Essays on Firms in International Trade

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To my beloved Youngjoo and Jiwon

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification at the University of Cambridge or any other institution. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. It does not exceed the prescribed word limit of 60,000 words.

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Minkyu Son
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Abstract

My PhD thesis broadly explores how a firm responds to a changing environment in international trade through three distinct topics. I examine how firms adjust their technology investment to foreign competition and demand, and how firm performance is affected by a global trade policy shock. And I investigate the dynamics of firms' choices of invoicing currencies for exports over time.

My first chapter - which builds on my PhD registration chapter and is developed further as a joint work with my supervisor Dr. Crowley and Dr. Han - studies how the choices of individual firms contribute to the dominance of a currency in global trade. Using a detailed administrative dataset for UK exporters' extra-EU trade over 2010-2016, we document strong evidence of two mechanisms that promote the use of a dominant currency: (1) prior experience: the probability that a firm invoices its exports to a new market in a dominant currency is increasing in the number of years the firm has used the dominant currency in its existing markets; (2) strategic complementarities: a firm is more likely to invoice its exports in the currency chosen by the majority of its competitors in a foreign destination market to stabilize its residual demand in that market. We show that the introduction of a fixed managerial cost into a model of invoicing currency choice yields dynamic paths of currency choice that match our empirical findings. We argue that these channels reinforce one another to drive and sustain dollar dominance in international trade.

My second chapter empirically examines the propagation of the US-China tariff to other 29 countries' exports to China in 2018-19. Using an industry-country specific measure of input-output linkages with China, I find that the US tariffs on Chinese imports had a significant adverse impact on other trading partners by dampening Chinese demand for foreign inputs. Evidence also suggests that the China's retaliatory tariffs against the US and its most-favoured-nation (MFN) tariff cuts during the same period positively affected other countries in non-intermediate goods. However, the negative upstream effect of the US tariffs prevails in magnitude, resulting in a substantial fall in aggregate export to China. Firm-level

analysis using a panel of Korean manufacturers lends further support to the importance of this vertical channel. The cross-border upstream propagation of local trade policy changes, as found in this chapter, illustrates how tightly productions are interconnected across countries and sectors, along with the rising importance of China in this global supply chain.

My third chapter investigates the innovation response to trade shocks using matched administrative datasets for UK firms' R&D expenditure and their trade exposures over 2002-2011. I find a strong adverse impact of import competition from China on UK firms' R&D, as supportive of 'Schumpeterian view'. No evidence is found that the improved access to Chinese inputs for individual firms offset this negative competition channel. Increased export demand, by contrast, significantly stimulates firms' R&D. There is also heterogeneity in R&D responses depending on the firms' initial conditions: (1) More productive firms increase their R&D by much more in response to export demand. (2) British exporters reduce R&D by less than non-exporters in the face of import competition from China. These findings together imply that innovation by purely domestic and less profitable firms was most hurt by globalization, leading to a widening productivity gap across firms.

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Chapter 1

Dominant currency dynamics: Evidence on dollar-invoicing from UK exporters

This chapter is co-authored with Dr. Meredith Crowley and Dr. Lu Han.

1.1 Introduction

The majority of international trade transactions are invoiced in a small number of currencies, with the US dollar being the dominant currency globally.[1] The last century witnessed the rise of the dollar as the globe's dominant currency, eclipsing the prior dominance of the British pound sterling.[2] A rich literature has sought to explain the factors contributing to the dollar's dominance in world trade; early contributions pointed to the relative macroeconomic stability of the US and its currency (Devereux and Engel (2002)), while more recent papers have focused on the importance of strategic complementarities in price-setting by firms in foreign markets (Goldberg and Tille (2008, 2016)) and hedging against the risk of changes to marginal cost due to imported inputs priced in foreign currencies (Chung (2016), Amiti, Itskhoki and Konings (2020), and Lyonnet, Martin and Mejean (2021)). However, due to

[1] Gopinath (2015) documents the dollar's share in global invoicing of trade was 4.7 (3.1) times its share in world imports (exports) for a sample of 43 (44) countries over 1999-2014.

[2] Eichengreen and Flandreau (2009) argue this shift took place as early at the 1920s; Chinn and Frankel (2008) discuss the evidence that the transition to dollar dominance was completed by 1945.

limited data on invoicing over time, the mechanism by which a particular currency comes to dominate the invoicing of world trade flows has remained something of a mystery.

While survey data from many countries suggests that the aggregate shares of invoicing currencies are relatively stable over time, this is not always the case.[3] In the space of just ten years, the share of British (extra-EU) exports invoiced in dollars rose 52.9%, from just under a third of (extra-EU) export value in 2010, to nearly half in 2019.[4] The large depreciation of the pound against the dollar in 2016 undoubtedly contributed to this shift, but does not tell the full story. Crucially, there was a steady and distinct rise in the use of the dollar for invoicing Britain's (extra-EU) exports *before* the sterling's 2016 depreciation; this rise is apparent not only in the share of (extra-EU) export *value* invoiced in dollars, which rose 16.9% over 2010-2015, but also in the share of (extra-EU) export *transactions* invoiced in dollars, which rose 18.7% between 2010 and 2015.[5]

This paper investigates the dynamic mechanisms behind the rise of a dominant currency. Our empirical analysis focuses on the previously unexplored choice of an invoicing currency to a new foreign market by firms with varying levels of tenure as exporters. Using the universe of export transactions from Her Majesty's Revenue and Customs (HMRC) Overseas Trade in Goods Database over 2010-2016, we document that a British firm's choice to invoice its exports to a *new* foreign market in dollars is *increasing* in its previous experience with dollar-invoicing to *other* foreign markets. We exploit this newly-identified feature of *extensive margin* invoicing patterns, in conjunction with evidence of strategic complementarities in British export pricing, to guide the development of a general framework of a firm's dynamic invoicing behaviour.

Our theoretical contribution is to introduce fixed costs associated with the management of foreign invoicing currencies into the firm's profit function. Intuitively, a firm that is strategically motivated to invoice in dollars in order to better maintain price stability relative to its (dollar-invoicing) competitors in one foreign market gains experience with dollar-

[3]See Ito and Chinn (2015), Ito and Kawai (2016), and Maggiori, Neiman and Schreger (2019) for a discussion of changing shares of invoicing currencies for international trade, all of which build upon earlier work by Goldberg and Tille (2008).

[4]The dollar-invoiced share of the UK's (extra-EU) exports was 31.0% (48.0%) in 2010 (2019). See Her Majesty's Revenue and Customs (2012, 2020). Notably, the dramatic ten-year shift in dollar-invoicing is not mirrored in Britain's (extra-EU) imports whose dollar share rose by a much more modest 5.7% over 2010-2019. Because the UK did not record the currency of invoice for its trade with the EU over this period, our analysis of invoicing currencies is limited to Britain's trade with non-EU countries.

[5]Authors' calculations based on Britain's (extra-EU) export value with a declared currency of invoice; the dollar share stood at 31.1% (36.7%) in 2010 (2015). See Her Majesty's Revenue and Customs (2012, 2016). The dollar share of Britain's extra-EU export transactions (among transactions with a declared currency of invoice) was 20.3% (24.1%) in 2010 (2015) (Calculated from data presented in Figure A1 in Corsetti, Crowley and Han (2020)).

invoicing; this experience, which is captured as increasing returns to scale deriving from the fixed costs of currency management, feeds into a higher likelihood of using the dollar in a firm's new foreign markets in subsequent periods. In this way, the two mechanisms of strategic complementarities and increasing returns to scale in currency management reinforce each other dynamically and strengthen the dominance of the dollar in global trade.

Understanding how and why a currency comes to dominate global trade is important from three perspectives. First, as recent research documents a close link between the currency in which a transaction is invoiced and the degree to which firms pass through exchange rate movements into import and domestic prices,[6] firms' invoicing choices are clearly a key to deciphering the global transmission of monetary and productivity shocks and to the setting of optimal policies.[7] Second, the path-breaking work of Gopinath et al. (2020) highlights the importance of dollar dominance as the source of asymmetric exchange rate pass-through across countries; investigating the dynamic roots of the 'Dominant Currency Paradigm' could help predict the rise of other dominant currencies. Third, a study of the dynamics of firms' invoicing choices sheds new light on the long-run effects of major policy changes or economic events, such as Brexit or Covid. Despite the importance of dominant currency dynamics, little progress has been made on the dynamics of invoicing choices due to data limitations.[8]

The UK presents an interesting case to study because its own currency, the pound sterling, was used for invoicing over 60% of British exports to extra-EU destinations in 2010, but this share had fallen dramatically to 41% by 2019 (see Her Majesty's Revenue and Customs (2012, 2020)). Previous work from Corsetti, Crowley and Han (2020) has documented interesting and important patterns in the use of invoicing currencies by British exporters; most notably, 99% of the UK's extra-EU export value originates from firms that use at least two currencies, 50% of export value originates from UK exporters that are using at least two different currencies to invoice sales of the same product to the same foreign destination within a calendar year, and finally, British exporters actively switch the currencies used to invoice exports over time. Altogether, this information tells us that invoicing currency

[6]See Gopinath, Itskhoki and Rigobon (2010), Boz, Gopinath and Plagborg-Møller (2019), Auer, Burstein, Erhardt and Lein (2019), Chen, Chung and Novy (forthcoming), Amiti, Itskhoki and Konings (2020), Corsetti, Crowley and Han (2020).

[7]The transmission of shocks in a open macroeconomic model depends on the currency in which the price is stable. For example, a stable local currency price would insulate a local economy against foreign shocks. See Goldberg and Knetter (1997), Corsetti and Pesenti (2005) and Burstein and Gopinath (2014) for more details.

[8]US data is not well-suited for this type of analysis as one cannot distinguish between producer versus vehicle currency invoicing by US exporters that invoice in dollars. Many countries' administrative datasets, such as the Belgium data used in Amiti, Itskhoki and Konings (2020), have recorded invoicing choices for only a limited time-span of one to two years.

is an active margin of choice for British exporters and examining the static and dynamic factors that influence British firms' choices could be informative about changes in the use of currencies around the globe and over time.

Empirically, we document two novel facts that are essential to understanding the dynamics of invoicing currency choices and the formation of a dominant currency. First, we analyse and document the role that previous successful experience with dollar-invoicing plays in future choices, focusing on a firm's choice of an invoicing currency when it enters a new foreign market. One year of dollar-invoicing in any of a firm's existing markets increases the probability of dollar invoicing in a new market by 4 percentage points relative to those firms that have never used the dollar in any market. Importantly, the probability of dollar invoicing in a new market is increasing in a firm's experience with the dollar – a firm with 6 years of dollar-invoicing experience is 14 percentage points more likely to invoice in dollars in a new market relative to those firms which have never invoiced in dollars. This evidence suggests the existence of a positive feedback channel of dollar invoicing that cannot be explained by existing models of invoicing currency choice.

Second, we document micro evidence on the role of complementarity in firms' invoicing choices. We find a one standard deviation increase in the dollar-invoicing share of a firm's competitors from the UK raises the probability of dollar-invoicing by 2.1 percentage points, corresponding to a 9.45% increase from the mean dollar invoicing probability in our estimation sample. Moreover, we estimate that the quantitative importance of strategic complementarity as a factor underpinning dollar invoicing is more pronounced for large firms and for less differentiated products, consistent with theoretical models of oligopolistic competition.

Consistent with findings in Chung (2016) and Amiti, Itskhoki and Konings (2020), we confirm a significant role of imported inputs in determining the invoicing currency for exports. A higher share of *imports* invoiced in dollars is associated with a higher likelihood of invoicing *exports* in dollars. In contrast, imports invoiced in other currencies – the euro in particular – reduce the probability of dollar-invoicing. This pattern is consistent with a practice in which firms hedge their exchange rate risk in dollars by aligning their export currency with their import currency.

Our novel theoretical contribution is a framework that incorporates the dynamics of invoicing currency choices and characterizes the necessary conditions under which the model can reproduce our newly documented empirical patterns. We show our framework of invoicing dynamics can be easily integrated with existing invoicing currency choice models through the dynamics of managerial costs. For example, if the cost of using dollars can be shared across the firm's dollar-invoiced destinations, the managerial cost of using dollars will be a decreasing function of a firm's dollar invoicing share in the past. Therefore, firms with a larger number of dollar-invoiced foreign export markets will be more likely to invoice in dollars in any new markets. More importantly, we show how the firm's invoicing choices change over time as a firm grows and how invoicing dynamics interact with entry dynamics to jointly determine the evolution of a dominant currency.

Altogether, our analysis identifies a firm's experience with dollars as an important channel contributing to the dollar's dominance. At the same time, it lends strong empirical support to theoretical works that have emphasized strategic complementarity and dollar-invoiced imported inputs as important factors associated with vehicle currency pricing (VCP).[9] The role of a firm's past experience with dollar-invoicing as a driver behind future choices has not been previously considered in the literature which, due to data limitations, has focused primarily on cross-sectional variation. Our results open up a new line of research exploring the evolution of invoicing choices over time and across destinations. This highlights the importance of the dynamic paths of individual firms' choices in the formation of a dominant currency.

Related literature. This paper builds on a rich theoretical and empirical literature on endogenous currency choices and their implications [Friberg (1998), Bacchetta and van Wincoop (2005), Engel (2006), Goldberg and Tille (2008, 2016), Mukhin (2018), Devereux, Dong and Tomlin (2017) and Lyonnet, Martin and Mejean (2021)]. An early contribution from Goldberg and Tille (2008) uses cross-country data on the aggregate shares of different invoicing currencies to analyse a theoretical model of a firm's strategic incentive to choose the same currency as other exporters.[10] More recent work has used large firm-level datasets to study the use of different invoicing currencies by firms. Amiti, Itskhoki and Konings (2020) study Belgian firms' trade with extra-EU destinations and document that larger firms are more likely to invoice in dollars while smaller, less import-intensive firms invoice in euros (i.e., producer currency pricing) and exhibit almost complete exchange rate pass-through into foreign import prices. To further this line of research, we present a framework for invoicing currency choice and examine both the existing channels of strategic complementarity and

[9]Theoretical models emphasizing strategic complementarity in invoicing currency choices include Bacchetta and van Wincoop (2005), Goldberg and Tille (2008), Mukhin (2018) and Gopinath et al. (2020). Additional papers focusing on strategic complementarities in pricing and exchange rate pass through include Gopinath and Itskhoki (2010, 2011), Auer and Schoenle (2016), and Pennings (2017).

[10]Their analysis emphasizes the prevalence of dollar pricing in homogeneous goods sectors as indirect evidence of a form of strategic complementarity that they refer to as the "coalescing motive"; that is, because demand for homogeneous products is more price-elastic than that for heterogeneous goods, the firms selling homogeneous goods have stronger incentives to stabilize their relative prices vis-a-vis their competitors and, hence, are more likely to price in dollars.

operational hedging as well as a novel dynamic channel that arises from the managerial cost of using a foreign currency.

The rest of the paper is organized as follows. Section 1.2 describes our data and presents new stylized facts on firm and transaction level invoicing choices. Section 1.3 outlines a theoretical framework. Section 1.4 discusses our empirical strategy. Section 1.5 presents our main estimation results. Section 1.6 discusses the aggregate implications of our findings. Section 1.7 concludes.

1.2 The evolution of invoicing currency use

In this section, we highlight the key features of our data and present three stylized facts on invoicing currency dynamics. The data used in our analysis, a seven year panel of transaction-level customs data from Her Majesty's Revenue and Customs (HMRC) Overseas Trade in Goods Database, enables us to document a series of important facts about a firm's use of different invoicing currencies *over time*. We exploit the long panel dimension to identify: (1) the role of export tenure in invoicing currency diversity; (2) the persistence of invoicing currency choices over time; and (3) the relationship between export tenure and a firm's dollar-invoicing share. These facts complement previous cross-sectional work that has examined within-period factors associated with invoicing currency usage, but adds important new features about the evolution of invoicing currency patterns over a firm's life-cycle.

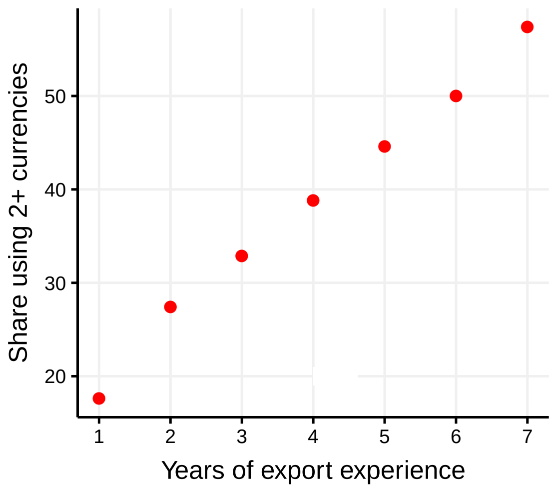
HMRC has recorded the invoicing currency for extra-EU trade transactions since January 2010. All importers must report their currency of invoicing for every transaction. Exporters whose annual exports exceed a value of £100,000 must report their invoicing currency for each transaction. For each transaction, the invoicing currency is recorded alongside an anonymous trader identifier, product and industry codes, country of origin and destination, and customs variables including values and quantities.[11] Given data availability, our analysis focuses on export transactions to extra-EU destinations over 2010-2016.[12]

Our first stylized fact is that experience in exporting is associated with the use of more currencies by UK firms. In figure 1.1, we present statistics that document that firms with more

[11] Products are defined by an 8-digit Combined Nomenclature (CN) code.

[12] Approximately fifty-three percent of UK goods exports were sent to extra-EU destinations over 2010-2016 (Calculated by the authors from HMRC Overseas Trade Statistics available at: https://www.uktradeinfo.com/trade-data/overseas/). When the currency of invoicing is not reported, we drop the corresponding observation. For instance, in 2015, the share of extra-EU exports from the UK which did not report the invoicing currency accounts for around 7.5% of export value and 31.0% of transactions. For extra-EU imports, observations for which no invoicing currency is reported account for a small fraction of transactions (less than 5%) and a trivial share of import value (0.1% or lower).

Fig. 1.1 Share of firms using 2 or more currencies given t years of exporting experience

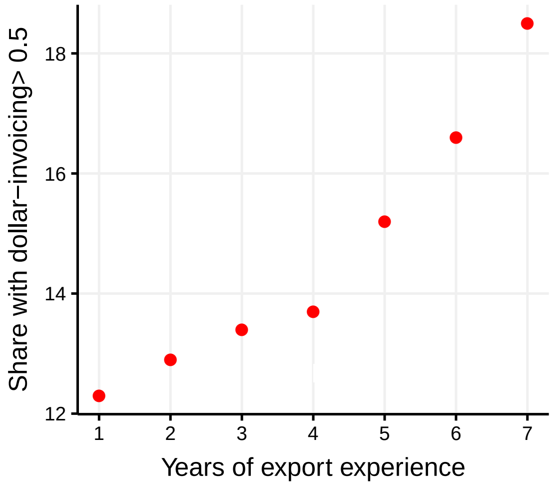


Notes: Each point represents the share of firm-year dyads using 2 or more currencies in a firm's tth year of exporting, given the the firm has t years of export experience over 2010-2016. The underlying data are reported in appendix table 1.C1, panel (a). Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

years of exporting experience tend to invoice their extra-EU exports in a larger number of currencies. For each firm, we calculate the joint distribution of years in which it is observed exporting and the number of currencies it uses in the tth year of exporting. Figure 1.1 presents the share of firms with t years of export experience that use two or more currencies in the tth year of exporting. The steady increase from 17.6% for firms with only one year of recorded exports over 2010-2016 to 57.4% for firms that exported in every year of the sample period indicates an important change over the lifespan of a firm. The statistics hint at the possibility that success in identifying valuable export markets increases the likelihood of success with using more currencies or, alternatively, that firms that know how to hedge risk via the use of multiple currencies are better able to survive as exporters. Our econometric analysis will tease out the factors behind this intriguing correlation.

The second stylized fact, depicted in figure 1.2, is that firms with more years of exporting experience tend to have a higher reliance on a specific currency – the US dollar – in invoicing their exports. For each firm, we plot the joint distribution of years in which it is observed exporting and the fraction of firms that invoice over 50% of their extra-EU exports in US dollars. Only 12.3% of firms with one year of export experience use dollars to invoice more than one-half of their exports. But the share of 'heavy dollar users' rises with exporting experience such that 18.5% of firms which report 7 years of dollar use over 2010-2016

Fig. 1.2 Share of firms invoicing over 50% of extra-EU exports in dollars given t years of exporting



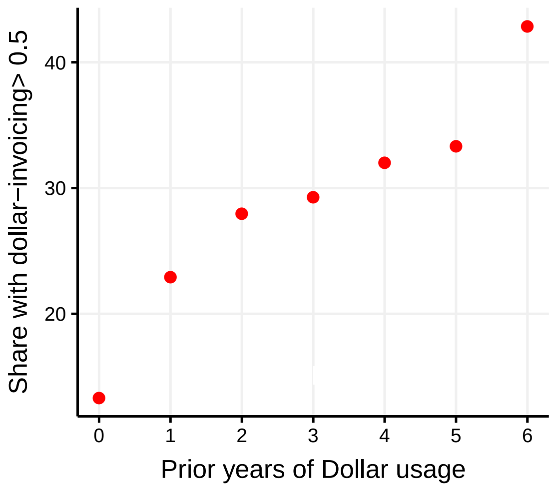
Notes: Each point represents the share of firm-year dyads invoicing more than one-half of extra-EU export value in dollars in a firm's tth year of exporting given the firm has t years of export experience over 2010-2016. The underlying data are reported in appendix table 1.C2, panel (a). Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

invoice more than one-half of their extra-EU exports in dollars. The fact that the share of firms which predominantly invoice in US dollars increases with exporting experience suggests the presence of firm-level economies of scale in the use of a currency which increase with a firm's duration of experience with the dollar.

Our final stylized fact relates the duration of dollar invoicing experience to a firm's dollar invoicing share. Figure 1.3 depicts a firm's prior years of dollar experience as of $t-1$ on the x-axis against the corresponding share of firm-year dyads which invoice over 50% of export value in dollars in year t. A substantial 42.8% of firms with 6 years of prior dollar-invoicing experience invoice over one-half of their exports in dollars. This is in stark contrast to the mere 13.3% of firms which predominantly use dollars even though they had no prior experience with dollar invoicing during our sample period.

To summarize, an exploration of the panel dimension of UK export transactions has revealed that firms with more years of export experience use a larger variety of invoicing currencies. Second, the share of firms that invoice more than half of their extra-EU exports in dollars increases in the firm's tenure as an exporter. Finally, the share of firms invoicing more than half of their extra-EU sales in dollars is increasing in the duration of a firm's previous experience with invoicing in dollars. Altogether, these facts paint a picture of how the use of

Fig. 1.3 Share of firms invoicing over 50% of extra-EU exports in dollars in year t given prior years of dollar invoicing



Notes: Each point represents the share of firm-year dyads invoicing more than one-half of extra-EU export value in dollars in year t given k years of dollar invoicing at $t-1$. The underlying data can be obtained from appendix table 1.C3, by dividing statistics in the sixth column of panel (a) by those in the seventh. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

a dominant currency grows with firm tenure in exporting, and more specifically, with tenure in dollar invoicing.

1.3 A model of currency choice

In this section, we propose a unified framework that incorporates the key elements of invoicing currency choices from the existing literature and captures the dynamic features of invoicing currency choices observed among the British firms in our data. The environment for currency choice is characterized by nominal rigidities in the spirit of previous contributions from Engel (2006), Goldberg and Tille (2008), Gopinath, Itskhoki and Rigobon (2010) and Mukhin (2018). We further allow for the presence of a managerial cost that varies with the firm's prior dollar invoicing experience.

1.3.1 Optimal flexible price

We begin with a firm's optimal pricing under flexible prices. On the production side, a firm uses labour and intermediate inputs from home and foreign countries to produce its output with a Cobb-Douglas production technology:

$$Y_f = A_f L_f^{1-\phi_f} \prod_{j=1}^{J} (M_{fj}^{\alpha_{fj}})^{\phi_f} \tag{1.1}$$

where Y_f denotes output, A_f is the exogenously given firm productivity, L_f is labour and M_{fj} are firm f's imports of intermediates invoiced in currency j. Constant returns to scale imply $\sum_{j=1}^{J} \alpha_{fj} = 1$. J denotes the set of currencies in which intermediate inputs are invoiced.

The firm faces a market structure featuring oligopolistic competition à la Atkeson and Burstein (2008) and Amiti, Itskhoki and Konings (2019). Specifically, each firm f produces a differentiated good in each industry and exports it to destination market d. Consumers in each destination have a nested CES demand over the varieties of goods. The elasticity of substitution within and across industries are ρ and η, respectively, with $\rho > \eta \geq 1$. The demand faced by a firm f in destination d is

$$Q_{fd} = P_{fd}^{-\rho} P_d^{\eta-\rho} D_d \tag{1.2}$$

where D_d is the exogenous demand shifter, P_{fd} is firm f's price in local (i.e., destination) currency and $P_d \equiv \left(\sum_f P_{fd}^{1-\rho}\right)^{\frac{1}{1-\rho}}$ is the aggregate price index in the destination. The firm's profit-maximizing price in local currency for each destination d is derived as

$$P_{fd} = \frac{\varepsilon(S_{fd})}{\varepsilon(S_{fd}) - 1} \frac{MC_f}{\xi_d} \tag{1.3}$$

where MC_f denotes the marginal cost derived from the firm's cost minimization problem and ξ_d is the level of the nominal exchange rate in units of producer currency relative to one unit of destination d currency. Note that the multiplicative markup ($\frac{\varepsilon_{fd}}{\varepsilon_{fd}-1}$) depends on the market share of individual firms (S_{fd}). Assuming that exchange rate movements are the only source of uncertainty, we can obtain the first-order approximation for the log optimal price p_{fd} around the non-stochastic steady-state as

$$p_{fd} \approx \frac{\Gamma_{fd}}{1+\Gamma_{fd}} p_{(-f)d} + \frac{1}{1+\Gamma_{fd}} \left(\sum_{j}^{J} \psi_f^j e_j - e_d \right) + \overline{C}_{fd} \tag{1.4}$$

where $p_{(-f)d} \equiv \sum_{k \neq f} \frac{S_{kd}}{1-S_{fd}} p_{kd}$ is the log of competitors' prices in local currency and $\Gamma_{fd} \equiv \Gamma(S_{fd}; \rho, \eta)$ denotes the markup elasticity with respect to prices. $\psi_f^j (= \alpha_{fj} \phi_f)$ is the share of imported inputs invoiced in each currency j which enters into firm f's production costs. e_d and e_j are the log exchange rates in units of producer currency relative to one unit of destination currency d and origin currency j, respectively. $\overline{C}_{fd}$ is a collection of non-stochastic terms.

1.3.2 Currency choice under nominal rigidities

We start by assuming the firm makes separate invoicing choices in each destination. Let $\mathbb{E}[\Pi^c_{fd}]$ denote firm f's expected profit in destination d if it has chosen currency c as its invoicing currency. For a given invoicing currency, the firm chooses its optimal one-period ahead pre-set price $\bar{p}^c_{fd}$ to maximize its expected operating profit $\mathbb{E}[\pi_{fd}(.)]$ denominated in its own home currency. The new element we introduce relative to a standard model in the literature is a managerial cost of using a foreign currency F^c_f.[13] The invoicing currency choice problem can be written formally as[14]

$$c = \underset{c}{\operatorname{argmax}}\, \mathbb{E}[\Pi^c_{fd}] = \underset{c}{\operatorname{argmax}} \left\{ \max_{\bar{p}^c_{fd}} \mathbb{E}\left[\pi_{fd}(\bar{p}^c_{fd} - e^c_d)\right] - F^c_f \right\} \tag{1.5}$$

where e^c_d is the log of the exchange rate in units of invoicing currency c relative to one unit of the destination currency d. The solution of the problem is characterized by a well-known theoretical result in the literature: the firm chooses the invoicing currency that most closely mimics its optimal flexible price and implements its desired degree of exchange rate pass through.[15]

Under a set of simplifying conditions detailed in appendix 1.A and using the optimal price expression (1.4), it can be shown that the expected profit of firm f exporting to destination d from using currency v relative to that from any arbitrary currency b has the following relationship:

$$\mathbb{E}[\Pi^v_{fd}] - \mathbb{E}[\Pi^b_{fd}] \propto \lambda_{fd} \Bigg[\underbrace{\frac{\Gamma_{fd}}{1+\Gamma_{fd}}(\zeta^v_{(-f)d} - \zeta^b_{(-f)d})}_{\text{Strategic complementarity}} + \underbrace{\frac{1}{1+\Gamma_{fd}}(\psi^v_f - \psi^b_f)}_{\text{Operational hedging}} \Bigg] - \underbrace{(F^v_f - F^b_f)}_{\text{Managerial cost}} \tag{1.6}$$

where Γ_{fd} is the markup elasticity with respect to the firm's own price; $\zeta^c_{(-f)d}$ is firm f's competitors' invoicing share of currency c in destination d; ψ^c_f is the firm's share of imports

[13] Several articles suggest the relevance of a managerial cost associated with invoicing in a foreign currency (Gopinath (2015) and Goldberg and Tille (2016)). Also see Lyonnet, Martin and Mejean (2021) for recent empirical evidence and a theoretical model for invoicing currency choices with financial hedging.

[14] We assume that there is no managerial cost of using the firm's own producer currency for invoicing. We also implicitly assume that the managerial cost of an invoicing currency is small enough such that it does not affect the firm's entry decision for each destination.

[15] See e.g., Engel (2006), Mukhin (2018) and Amiti, Itskhoki and Konings (2020).

invoiced in currency c; and $\lambda_{fd} > 0$ is a non-stochastic term related to the second derivative of the operational profit function detailed in appendix 1.A. The firm will choose currency v over currency b if the difference in expected profits is positive.

Equation (1.6) highlights three key mechanisms behind invoicing choices. The first element in the square brackets of equation (1.6) is related to strategic complementarities in pricing. Under nominal rigidities, the firm chooses the invoicing currency that is predominantly used by its competitors in order to keep its relative prices, and thereby its market shares, stable in the presence of exchange rate shocks. Note that the strength of the strategic complementarity in invoicing is governed by the markup elasticity (Γ_{fd}) which encapsulates two sources of heterogeneity to this strategic motive. The first heterogeneity is related to the firm's size. Since the markup elasticity (Γ_{fd}) has a hump-shaped relationship with the firm's market share (S_{fd}) for given parameters ρ and η, so does the extent of the strategic complementarity. Empirically, for realistic market shares (i.e., market shares below 80%), the markup elasticity monotonically increases with the market share. The second heterogeneity is related to the level product differentiation, which, in turn, is governed by the elasticity of substitution within an industry (ρ). If a product is less differentiated and thus demand is more price-elastic, changes in relative prices due to exchange rate movements induce larger profit changes. This, in turn, implies that firms exporting less differentiated goods would have a stronger incentive to stabilize their relative prices against exchange rate shocks by matching the invoicing currency of their competitors in the destination.

The second element in square brackets of equation (1.6) captures a firm's operational hedging motive. All else equal, firms would prefer to match their export currency with that of their imported inputs since this would provide an 'effective hedge' on exchange rate risk from importing inputs.

The third factor determining the choice of an invoicing currency is the managerial cost of using a particular currency; a higher managerial cost is associated with a lower probability of choosing the currency. The managerial cost captures various costs of managing exchange rate risk and writing contracts for delivery in foreign currencies; it could include hiring staff or services of a currency management firm.

1.3.3 Invoicing dynamics arising from managerial costs

In this section, we elaborate on the element of managerial cost and explain how invoicing choices evolve under different assumptions about the functional form of the managerial cost given an assumed process of firm entry into new markets.

To keep our model as tractable as possible, we assume firms start with no exporting experience. Each firm adds one foreign market in each period.[16] We further assume, after controlling for the observable factors of strategic complementarity $\boldsymbol{\zeta}_{(-f)d}$, and operational hedging $\boldsymbol{\psi}_{fd}$, expected operational profit of using the US dollar (the local currency) relative to the producer's currency is uniformly distributed for each destination:[17]

$$\begin{aligned} &\mathbb{E}[\pi_{fd}^{\mathrm{USD}} - \pi_{fd}^{\mathrm{PCI}} | \boldsymbol{\zeta}_{(-f)d}, \boldsymbol{\psi}_{fd}] \sim U(0,1) \\ &\mathbb{E}[\pi_{fd}^{\mathrm{LCI}} - \pi_{fd}^{\mathrm{PCI}} | \boldsymbol{\zeta}_{(-f)d}, \boldsymbol{\psi}_{fd}] \sim U(0,1) \end{aligned} \tag{1.7}$$

If the firm makes its invoicing choice in each market without regard for its choice in other markets, then it will use dollars in a new destination d if the expected benefit of using the dollar is larger than the benefit of (1) using the producer's currency and (2) the local currency:

$$\begin{aligned} &\mathbb{E}(\Pi_{fd}^{\mathrm{USD}}) - \mathbb{E}(\Pi_{fd}^{\mathrm{PCI}}) = \mathbb{E}[\pi_{fd}^{\mathrm{USD}} - \pi_{fd}^{\mathrm{PCI}} | \boldsymbol{\zeta}_{(-f)d}, \boldsymbol{\psi}_{fd}] - (F_f^{USD} - 0) > 0 \quad \text{and} \\ &\mathbb{E}(\Pi_{fd}^{\mathrm{USD}}) - \mathbb{E}(\Pi_{fd}^{\mathrm{LCI}}) = \mathbb{E}[\pi_{fd}^{\mathrm{USD}} - \pi_{fd}^{\mathrm{LCI}} | \boldsymbol{\zeta}_{(-f)d}, \boldsymbol{\psi}_{fd}] - (F_f^{USD} - F_f^{LCI}) > 0 \end{aligned} \tag{1.8}$$

A direct implication of (1.8) is that, if the managerial cost is fixed and paid separately in each destination, there will be no time or path dependency in the choice of an invoicing currency. For example, if $F_f^{USD} = F_f^{LCI} = \kappa_0$, then the probability of using the dollar in a new market is the same as the probability of using the local currency, which is equal to $1/2[1-(\kappa_0)^2]$. A constant probability means that, controlling for the observable factors of strategic complementarity and operational hedging, the firm's invoicing currency decision in a new market is independent from the firm's previous invoicing choices in its existing markets. Note that this conclusion relies on the assumption that the fixed cost of currency management is specific to each individual foreign market; there are no cross-market returns to scale.

We believe it is more realistic to assume that the managerial cost of using a currency is firm-specific, rather than firm and destination-specific. This would imply the fixed cost of currency management could be shared across destinations. Once the cost is paid, then

[16] This assumption is useful for deriving the theoretical relationships. Our quantitative simulation results hold with alternative entry and exit patterns.

[17] We have assumed a 0-1 uniform distribution for simplicity and convenience. Our discussions and key results hold for alternative normal distributions or uniform distributions with a different support. We can always adjust the level of the managerial cost to match the empirical statistics. For example, the assumption of a $U(-0.5, 0.5)$ distribution with a managerial cost of 0.5 is equivalent to the assumption of a $U(0,1)$ distribution with a managerial cost of 0.

the firm can use the currency in any of its markets in the period. In this case, the actual managerial cost incurred in each destination is a function of the number of destinations using that currency. That is,

$$F_{ft}^{c} = \frac{\kappa_0}{\sum_d \mathbb{1}_{fdt}^{c}} \tag{1.9}$$

where $\mathbb{1}_{fdt}^{c}$ equals one if the firm uses currency c in destination d at time t. In this specification, the fixed cost of using currency c in period t in each foreign destination declines with each additional market in which the firm uses currency c. The shared managerial cost provides an incentive by which the firm's optimal choice of a currency in destination d is linked to its choices of currencies in all other destinations. That is, the firm chooses to use the dollar in a set of markets $\mathscr{D}_{ft}$ if $F_{ft}^{\text{USD}} = \kappa_0 / \sum_{d \in \mathscr{D}_{ft}} \mathbb{1}_{fdt}^{\text{USD}}$ and

$$\begin{aligned} &\mathbb{E}(\Pi_{fd}^{\text{USD}}) - \mathbb{E}(\Pi_{fd}^{\text{PCI}}) > 0 \quad \text{and} \quad \mathbb{E}(\Pi_{fd}^{\text{USD}}) - \mathbb{E}(\Pi_{fd}^{\text{LCI}}) > 0 \quad \forall d \in \mathscr{D}_{ft} \\ &\mathbb{E}(\Pi_{fd}^{\text{USD}}) - \mathbb{E}(\Pi_{fd}^{\text{PCI}}) \leq 0 \quad \text{or} \quad \mathbb{E}(\Pi_{fd}^{\text{USD}}) - \mathbb{E}(\Pi_{fd}^{\text{LCI}}) \leq 0 \quad \forall d \notin \mathscr{D}_{ft} \end{aligned} \tag{1.10}$$

Under this set-up, an interesting dynamic pattern of invoicing choices arises when the firm expands by adding new markets. First, as the number of markets that it serves increases, the firm is more likely to use dollars. Second, the firm is more likely to use dollars in a new market if it has lots of existing dollar markets. This means, if we trace the invoicing choices of the same firm over time, we will see interesting path dependence in the firm's invoicing choices. The firm that happened to enter a dollar heavy market in the earlier stage of its life will be more likely to use dollars in all of the subsequent markets it enters.

While the model gives interesting dynamics of invoicing choices, the joint invoicing decision problem can be only solved computationally rather than analytically. Supported by the simulation results, we proxy the theoretical evolution of the managerial costs suggested by (1.9) and (1.10) with the following reduced-form representation:

$$F(\omega_{ft-1}^{c}) = \kappa_1 - \kappa_2 \cdot \omega_{ft-1}^{c} \tag{1.11}$$

where ω_{ft-1}^{c} is the invoicing share of currency c in firm f global exports in period $t-1$; κ_1 such that $0 < \kappa_1 < 1$ represents the initial cost invoicing in currency c; and κ_2 such that $0 < \kappa_2 < \kappa_1$ represents the degree of cost reduction due to prior usage. This cost reduction could be due to effective cost sharing across destinations or more generally a result of accumulated know-how of conducting a foreign currency transaction and/or managing foreign exchange risk. Similar to (1.9), as the firm adds more dollar markets, $\omega_{ft-1}^{\mathrm{USD}}$ would tend to rise, which subsequently reduces the cost of dollar invoicing in a new market.

Using equations (1.7), (1.8) and (1.11), the probability of dollar invoicing in a new market can be derived analytically as:

$$T(\omega_{ft-1}^{\mathrm{USD}}) = \frac{1}{2}(1+\kappa_2\omega_{ft-1}^{\mathrm{USD}})^2 - \frac{1}{2}(\kappa_1)^2 \tag{1.12}$$

Fig. 1.4 Dollar transition function

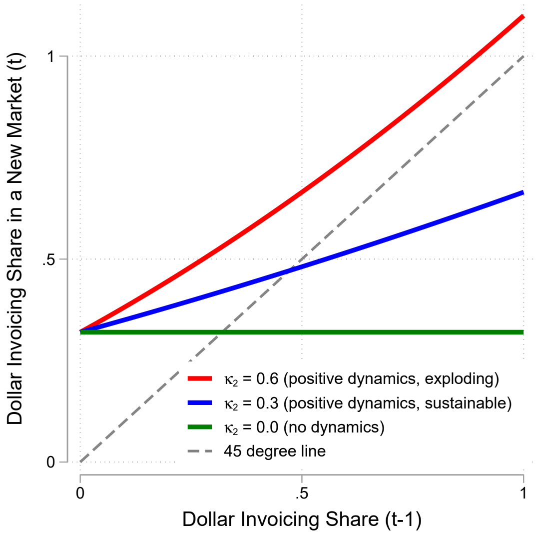


Figure 1.4 gives an illustration of this simple function when the initial cost parameter κ_1 is set to 0.6. As shown by the dark green horizontal line, when $\kappa_2 = 0$, the dollar invoicing probability in the new market is constant and does not depend on the firm's dollar invoicing share in the last period. Interesting dynamics which relate the choice of an invoicing currency for a new market to a firm's prior share of exports invoiced in dollars arises when $\kappa_2 > 0$. Figure 1.4 depicts two important cases in which κ_2 is greater than zero. In the first case, represented by the blue line, the dollar invoicing share will be sustained at a particular level. As can be seen from the blue line of figure 1.4, the firm's dollar invoicing share will increase (decrease) if its last period's dollar invoicing share was low (high). The dollar invoicing share will eventually stabilize around the interaction between the blue line and the 45 degree line.[18] The second important case occurs when the cost reduction (κ_2) is large relative to the fixed component κ_1 (i.e., $\kappa_2 > -1+\sqrt{2+(\kappa_1)^2}$). As shown in the red line, the model

[18]The steady-state dollar share is given by $\overline{\omega}^{\mathrm{USD}} = \frac{1-\kappa_2-\sqrt{(\kappa_1\kappa_2)^2-2\kappa_2+1}}{(\kappa_2)^2}$.

converges into a dollar only equilibrium, where all firms use dollars in all destinations. The dollar transition function (1.12) directly governs the relationship between the probability of dollar invoicing in a new market and the firm's prior dollar experience, which we discuss next.

Dollar invoicing probability in a new market and the firm's dollar invoicing experience

In this subsection, we characterize the relationship between the firm's probability of dollar invoicing in a new market and its prior dollar invoicing experience and compare the predictions of models with different managerial cost structures through Monte Carlo simulations. We present a general theoretical framework in Appendix 1.A.4.

Specifically, we present the simulation predictions of the relationship between the dollar invoicing probability in a new market and a firm's prior dollar experience from four different models. The first model takes our reduced form assumption of the managerial cost in equation (1.11), where we calibrate $\kappa_1 = 0.6$ and $\kappa_2 = 0.18$.[19] The second model uses the shared global managerial cost setting in (1.9), where we calibrate κ_0 such that the model gives a similar cost function of the reduced form managerial cost model. The third model considers a one-off global sunk cost of using a currency. For example, the company may encounter a small fee in setting up a US dollar account. The cost of using a currency assumed to be 0 if the firm has used this currency in any of its existing markets in the past and κ_0 otherwise.[20] Finally, the fourth model assumes a fixed transaction cost – the firm pays a fixed cost for each destination that uses a foreign currency. Notably, the fixed transaction cost model can be thought of as a special case of our reduced form model where $\kappa_2 = 0$.

For each model, we simulate 200,000 firms with 10 destinations over 10 time periods according to the data generating process specified in (1.7). All firms start with no exporting market, add one foreign market in each period and end up with exporting to 10 destinations in period 10. We drop the first 3 periods of the simulated data to reflect the fact that we do not observe the full dynamics of firms in our empirical data.[21]

Figure 1.5 shows the predicted relationships between the dollar invoicing probability in a new market and the firm's prior dollar experience measured by the "Dollar Spell Length",

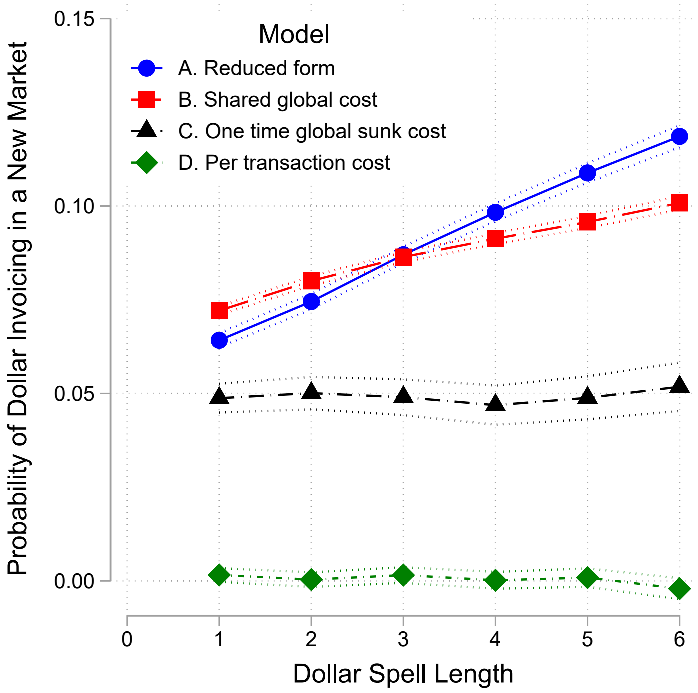
[19]As it will be clear in the later sections, this calibration matches our empirical estimates reasonably well.

[20]More formally,

$$F^c_{fdt} = \begin{cases} \kappa_0 & \text{if} \quad \sum_{\tau=0}^{t-1} \sum_d \mathbb{1}^c_{fd\tau} = 0 \\ 0 & \text{if} \quad \sum_{\tau=0}^{t-1} \sum_d \mathbb{1}^c_{fd\tau} > 0 \end{cases}$$

[21]HMRC only started collecting the detailed information on invoicing currency of transactions in 2010. We therefore do not observe the full dynamics of invoicing currency choices for firms started exporting before 2010.

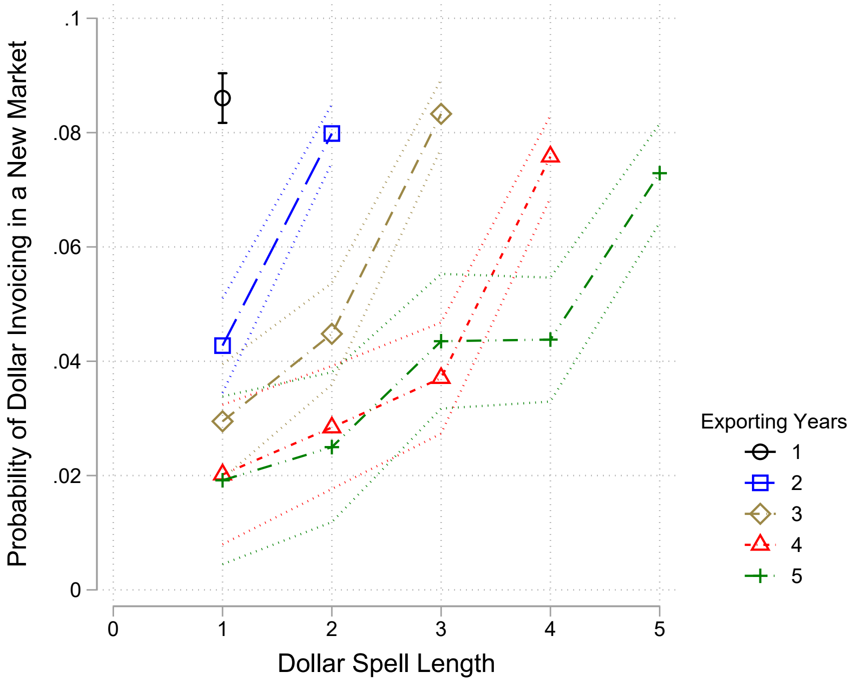
Fig. 1.5 Comparison of predictions: Dollar invoicing probability in a new market and prior dollar experience



Notes: This figure compares the relationship between the dollar invoicing probability in a new market and the prior years of dollar experience at a firm ("Dollar Spell Length") of the four managerial cost models described in the text. The dashed lines indicate the 90% confidence interval of the estimates.

which is defined as the number of years the firm has invoiced any foreign sales in dollars prior to its entry into the new market. We can see the probability of dollar invoicing is increasing in the dollar spell length for models A and B. As the firm adds more dollar markets and becomes more experienced in dollar-invoicing, the cost of using the dollar goes down and the firm is more likely to use dollars in the new market. In contrast, in models C and D, the probability of dollar-invoicing is constant and does not depend on the firm's prior dollar experience. Especially, in model C with the one time global sunk cost, the dollar invoicing probability jumps to $\kappa_0 = 0.05$ once the firm has used the dollar in any of its existing markets but this probability does not change over time as the firm becomes more experienced in dollar invoicing. As shown in section 1.5.2, our empirical results show a clear positive relationship between the dollar invoicing probability in the new market and the dollar spell length and thus rejects models of C and D.

Fig. 1.6 Dollar invoicing probability and prior dollar experience by exporting year cohort



Notes: This figure presents estimates by the number of exporting years from simulated data of our reduced form model. We calibrate $\kappa_1 = 0.6$ and $\kappa_2 = 0.18$. The dashed lines indicate the 90% confidence interval of the estimates.

Figure 1.6 shows the predicted relationship between the dollar invoicing probability in a new market and the dollar spell length by the number of exporting year cohort from the model with the reduced form managerial cost.[22] Firstly, we can see the positive relationship between the dollar invoicing probability and dollar spell length holds within each exporting year cohort, suggesting the positive relationship predicted in models A and B of figure 1.5 is not entirely driven by mixtures of firms of different ages. Secondly, comparing the estimates vertically, we can see the effect of one additional year of dollar experience decreases in the number of exporting years.[23] Intuitively, for a firm that has been exporting for many years but only used dollar for one or two years, the realized benefit of using the dollar must be very low in the firm's existing markets. Therefore, the probability that the dollar cost in a new market can be shared with the existing markets is relatively low for the firm.

1.4 Empirical strategy

To test the predictions laid out in the previous section, we exploit the invoicing currency information of UK exports to extra-EU countries over 2010-2016 and estimate the probability of invoicing in dollars at the firm-product-destination-year level. Throughout our analysis, we report estimates of linear probability models.

1.4.1 Strategic complementarities and operational hedging

We start by testing the importance of the two static determinants of invoicing currency: strategic complementarities and operational hedging. Specifically, we estimate:

$$\mathbb{1}^{\text{USD}}_{fhdt} = \beta_1 \zeta^{\text{USD}}_{(-f)idt} + \beta_2 \psi^{\text{USD}}_{ft} + \beta_3 \psi^{\text{Euro}}_{ft} + \beta_4 \psi^{\text{LCI}}_{ft} + \gamma \text{TOTEXP}_{ft} + \text{FEs} + \nu_{fhdt} \quad (1.13)$$

where the subscripts f, h, i, d and t denote a firm, an 8-digit CN product, a more aggregated 6-digit industry (to which the product h belongs), a destination market, and a transaction year, respectively. $\mathbb{1}^{\text{USD}}_{fhdt}$ is a dummy variable equal to one if the invoicing currency is US dollars and zero otherwise. Subscript $(-f)$ indicates all other UK firms excluding firm f. The explanatory variable related to strategic complementarity is $\zeta^{\text{USD}}_{(-f)idt}$, defined as the dollar invoicing share of firm f's competitors *from the UK* in destination d in year t at the 6-digit industry i level:

$$\zeta^{\text{USD}}_{(-f)idt} = \frac{\sum_{k \neq f} \text{Export}^{\text{USD}}_{kidt}}{\sum_c \sum_{k \neq f} \text{Export}^{c}_{kidt}}$$

[22] The figure for the shared global cost model is very similar to the one presented here.

[23] See equations (1.A15)-(1.A17) in Appendix 1.A.4 for the theoretical relationships.

where Export^{c}_{fidt} is firm f's export value invoiced in currency c (measured in sterling) in 6-digit industry i to country d in year t. The operational hedging motive is captured by ψ^{c}_{ft} which is the share of currency $c \in \{\text{USD}, \text{Euro}, \text{LCI}\}$ in firm f's imports in year t (measured in sterling):[24]

$$\psi^{c}_{ft} = \frac{\text{Import}^{c}_{ft}}{\sum_c \text{Import}^{c}_{ft}}$$

where Import^{c}_{ft} is firm f's total import value invoiced in currency c (measured in sterling) in year t. In addition to these main variables of interest, we control for firm size (TOTEXP_{ft}) with the logarithm of the total export value of firm f at time t across all destinations. This is based on the argument that, irrespective of the factors above, large exporters would be more likely to use a foreign currency as they are better able to handle exchange rate risk (Lyonnet, Martin and Mejean, 2021). We also include 8-digit product-year fixed effects and destination-year fixed effects to control for any time-invariant product and country characteristics as well as product- and country-specific demand changes that could separately affect a firm's currency choice.

1.4.2 The endogeneity of competitors' currency choices

One concern regarding the baseline specification is the potential endogeneity of the UK competitors' dollar invoicing share ($\zeta^{\text{USD}}_{(-f)idt}$). If strategic complementarity indeed exists, firm f's decision to invoice in dollars likely affects other UK firms' currency choices. To address this issue, we construct two instruments to isolate the variation in the competitors' currency choices that are due to the competitors' own existing characteristics and are unlikely to be affected by the current invoicing choices of firm f. In particular, we exploit differences in competitors' cost structures and construct measures of the UK competitors' dollar import share ($\psi^{\text{USD}}_{(-f)idt}$).[25] We also include the UK competitors' average firm size ($\text{TOTEXP}_{(-f)idt}$)

[24]Note that the term ψ^{c}_{ft} in the model indicates the imported inputs in each currency as a share of total production costs. But the variable ψ^{c}_{ft} in our empirical analysis does not exactly match the theory as it is measured as a share of total imported inputs because firm-level data on the total wage bill and total materials costs is not available in our dataset. This variable captures the (relative) importance of a certain currency in a firm's importing of inputs.

[25]This IV strategy is conceptually similar to the work of Amiti, Itskhoki and Konings (2019) on Belgian firms' domestic pricing that exploits the competitor's marginal cost as an instrument for the competitor's price.

as an additional instrument. Thus, our two instruments are:

$$\psi^{\mathrm{USD}}_{(-f)idt} = \sum_{k\neq f} \frac{S_{kidt}}{1-S_{fidt}} \times \psi^{\mathrm{USD}}_{kt}$$

$$\mathrm{TOTEXP}_{(-f)idt} = \sum_{k\neq f} \frac{S_{kidt}}{1-S_{fidt}} \times \mathrm{TOTEXP}_{kt}$$

where S_{fidt} denotes firm f's export share in a 6-digit industry i to destination d in year t among all UK firms:

$$S_{fidt} = \frac{\mathrm{Export}_{fidt}}{\sum_i \mathrm{Export}_{fidt}}.$$

1.4.3 Dynamics: Dollar invoicing in new destinations

Lastly, we examine whether the managerial cost of using a particular currency depends on a firm's past experience of using that currency. We introduce two firm-level measures to investigate how previous invoicing behaviour in existing markets impacts the invoicing choices in a new destination, i.e., (1) the total number of years that a firm has invoiced any export sales in dollars before it enters a new destination and (2) the dollar invoicing share in the firm's total exports in the year before entering a new destination. To distinguish the dynamic impact of the previous dollar invoicing experience from simple inertia caused by, for example, long-term contracts, we focus our analysis on a firm's exports to a *new* destination. We control for potential confounding factors such as competitors' dollar invoicing share, the currency of imports, and firm size, as in the baseline case. The new entry specification is then given by:

$$\begin{aligned}\mathbb{1}^{\mathrm{USD}}_{fhdt} = {} & \beta_1 \zeta^{\mathrm{USD}}_{(-f)idt} + \beta_2 \psi^{\mathrm{USD}}_{ft} + \beta_3 \psi^{\mathrm{Euro}}_{ft} + \beta_4 \psi^{\mathrm{LCI}}_{ft} \\ & + \left(\sum_{l=0}^{6} \eta_l Spell^{\mathrm{USD},l}_{ft-1} \text{ or } \delta \omega^{\mathrm{USD}}_{ft-1} \right) + \gamma \mathrm{TOTEXP}_{ft} + \mathrm{FEs} + \nu_{fhdt} \end{aligned} \tag{1.14}$$

where $Spell^{\mathrm{USD},l}_{ft-1}$ is a dummy variable equal to one if the firm used dollars for l years prior to entering the new market (and zero otherwise) and $\omega^{\mathrm{USD}}_{ft-1}$ is the dollar export share of firm f in the year before entering the new market.

1.5 Estimation Results

Our analysis documents that strategic complementarity and operational hedging are important factors driving the choices of invoicing currencies for exports among British firms. We also document our novel findings on the important role that a firm's previous dollar invoicing has on its currency choice in a new destination.[26]

1.5.1 Strategic complementarities and operational hedging

Table 1.1 Dollar invoicing probability: Baseline

	(1) OLS	(2) OLS	(3) OLS	(4) IV
UK competitors' dollar invoicing share	0.319***	0.041***	0.026***	0.076***
	(0.001)	(0.001)	(0.001)	(0.004)
Dollar import share			0.164***	0.164***
			(0.000)	(0.000)
Euro import share			-0.009***	-0.009***
			(0.001)	(0.001)
Destination currency import share			-0.018***	-0.018***
			(0.001)	(0.001)
Firm size			0.016***	0.016***
			(0.000)	(0.000)
Observations	4,719,628	3,052,546	4,719,628	4,719,628
Adjusted R^2	0.0468	0.288	0.149	-
Firm-Product-Year FE		✓		
Country-Year FE		✓	✓	✓
Product-Year FE			✓	✓
Hansen J-stat [p-value]	-	-	-	0.156 [0.693]
Weak IV F-stat	-	-	-	69,591

Notes: The dependent variable is the dollar invoicing probability at the firm-product-destination-year level. Columns 1-3 present OLS results while column 4 is the result using 2SLS. Weak IV F-statistic denotes Kleibergen-Paap Wald rk F-statistic. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Table 1.1 reports the benchmark results for the dollar invoicing probability of UK exporters. Columns 1 to 3 are based on simple OLS regressions. Column 1 includes the dollar invoicing share of a firm's British competitors as an explanatory variable with no fixed effects,

[26] Summary statistics of variables used in our estimation sample are reported in appendix table 1.B1.

while column 2 adds firm-product-year and destination-year fixed effects. Both regressions show a significant positive effect of the UK competitors' dollar invoicing share. These indicate that firms are more likely to invoice in dollars if more UK competitors use dollars in the destination. Column 3 includes the shares of each invoicing currency in a firm's imports to capture the hedging motive and firm size as well as product-year and destination-year fixed effects. The influence of the competitors' currency choices becomes smaller but still remains significant.

A concern with these OLS results is that they do not account for potential endogeneity of the competitors' dollar invoicing which would bias the estimates. In column 4, we adopt the same specification as in column 3, but implement 2SLS using the competitors' average dollar import share and the competitors' average firm size as instruments for the competitors' dollar invoicing share for exports.[27] Column 4 confirms the significant influence of the competitors' dollar invoicing. In comparison to the OLS result in column 3, the coefficient becomes larger, signalling a downward bias when endogeneity is not controlled for. To quantify the magnitude, a one standard deviation rise in the UK competitors' dollar invoicing share leads to an increase in the firm's own dollar invoicing probability of 2.1 percentage points (=0.285*0.076). This magnitude corresponds to 9.45% increases (0.229→0.250) from the mean dollar invoicing probability in the sample. To sum up, these results lend support to the hypothesis that strategic complementarity influences firms' currency choices; that is, firms keep their relative prices stable vis-a-vis their competitors by picking the same invoicing currency as the majority of their competitors in the market.

Turning to operational hedging, the firm's import currency composition also plays a significant role in determining its invoicing currency for exports. In all specifications, a higher share of imports invoiced in dollars is associated with a higher chance of invoicing exports in dollars. In column 4, a one standard deviation rise in a firm's dollar import share is associated with an increase in their dollar invoicing probability for exports of 6.4 percentage points (=0.164*0.391). On the other hand, a higher share of imported inputs in alternative currencies – euros or a destination currency – decreases the dollar invoicing probability, which is also in line with the prediction.

Finally, we find that firm size – measured by a firm's total export value – is an important driver for dollar invoicing. Regarding the fact that the majority of UK firms invoice their

[27] The first-stage regression result is reported in table 1.B2 in the appendix. Both instruments are strongly and positively correlated with the competitors' dollar invoicing shares. Regarding the validity of our instruments, a Hansen J-test does not reject the null of over-identification at a conventional level while the null of a weak instrument is strongly rejected.

exports in sterling (i.e., the producer's currency in the UK), this result is consistent with the prior literature that large firms are more likely to use foreign currencies.

Heterogeneity in strategic complementarity: market share and product differentiation

We highlight two sources of heterogeneity in strategic complementarity. First, firms with larger market shares in a destination have a stronger strategic motive to invoice in the same currency as their competitors. To see this, we split our sample into 'large' and 'small' firms at the median of firms' market shares among UK exporters within an industry and a foreign destination and implement 2SLS in each sub-sample (see table 1.2). Column 1 gives the baseline results previously reported in column 4 of table 1.1. Columns 2 and 3 report the results from the sub-samples for large and small firms, respectively. Consistent with the theory, larger firms exhibit a stronger tendency to align their currency with their competitors relative to smaller firms (0.100 vs 0.046).[28]

In table 1.3, we examine whether the strength of strategic complementarity varies with the extent of product differentiation. Columns 1 and 2 split our dataset into sub-samples according to the product classification system of Rauch (1999). Homogeneous goods which are 'traded on an organized exchange' exhibit stronger strategic complementarities (0.198) relative to goods that Rauch classifies as 'differentiated' (0.075).[29] This leads us to employ the new product classification introduced by Corsetti, Crowley, Han and Song (2018) which is constructed from the use of different types of Chinese measure words in Chinese customs data. Column 3 reports results for a subsample of less differentiated manufactured goods that are identified by the use of continuous measures such as kilograms on customs forms. In column 4, estimates for products that use measure words that indicate that they are discrete items, such as televisions or motorcycles, are reported. Under this classification, the analysis shows strategic complementarities are stronger when goods are less differentiated. We estimate firms selling less differentiated products (0.091) are more responsive to competitors' dollar invoicing than those selling highly differentiated products (0.043).

[28] One might argue that if we follow the theoretical relationship in equation (1.6) more strictly, we should expect the coefficients on imported inputs – particularly dollar-invoiced imports – to be larger for small market share firms. But as noted in footnote 24, our measure of imported inputs in each currency does not fully correspond to ψ^c_{ft} in the model since it is measured as a share of total imported inputs rather than a share of total production costs.

[29] An alternative interpretation is that goods 'traded on an organized exchange' are highly concentrated in commodities such as petroleum where the dollar's prevalence in these goods is not directly related to product homogeneity. Instead, as Eichengreen, Chiţu and Mehl (2016) argue, the dollar's prevalence would be simply due to the fact that the US is among the largest suppliers of oil-related products and most of the US firms price in dollars.

Table 1.2 Dollar invoicing probability: Market share heterogeneity

	(1) Baseline	(2) Large	(3) Small
UK competitors' dollar invoicing share	0.076***	0.100***	0.046***
	(0.004)	(0.005)	(0.006)
Dollar import share	0.164***	0.163***	0.160***
	(0.000)	(0.001)	(0.001)
Euro import share	-0.009***	-0.012***	-0.012***
	(0.001)	(0.001)	(0.002)
Destination currency import share	-0.018***	-0.042***	-0.010***
	(0.001)	(0.002)	(0.001)
Firm size	0.016***	0.013***	0.018***
	(0.000)	(0.000)	(0.000)
Observations	4,719,628	2,359,085	2,354,927
Country-Year FE	✓	✓	✓
Product-Year FE	✓	✓	✓
Hansen J-stat [p-value]	0.156 [0.693]	0.003 [0.956]	2.389 [0.122]
Weak IV F-stat	69,591	36,632	39,551

Notes: The dependent variable is the dollar invoicing probability at the firm-product-destination-year level. All the results are based on 2SLS. Column 1 shows the baseline results from column 4 of table 1.1. Columns 2 and 3 are the results using the sub-samples for large and small firms according to the median of firms' market share within an industry, destination, and year. Robust standard errors in parentheses. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

1.5.2 Dynamic evolution in currency choice

In this subsection, we explore whether a firm's previous dollar invoicing intensity in existing markets affects its currency choice in a new destination using a sample of entrants into new destinations. Figure 1.7 illustrates a key finding: firms which have more historical experience with dollar-invoicing are more likely to invoice in dollars in a new destination. As seen in the figure, the probability of invoicing in dollars in a new destination market in year t increases with the number of years of dollar-invoicing experience in existing markets as of time $t-1$, the last period before entry.

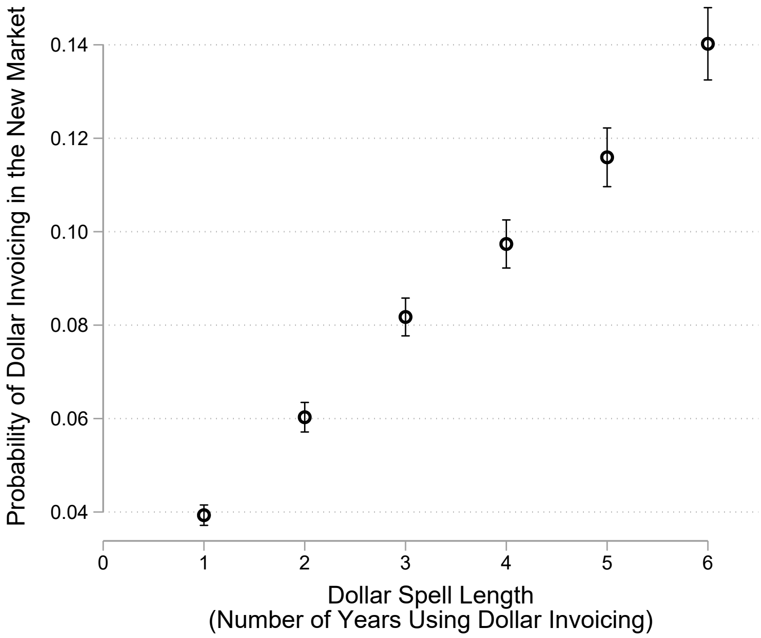
We present estimates from our empirical model of new market entry (1.14) in table 1.4. With entry into a new destination, we find evidence of strategic complementarities and operational hedging in the choice of an invoicing currency for exports. Interestingly, one exception is operational hedging in relation to imported inputs invoiced in the local currency of the export destination (in the fourth row of table 1.4). That is, firms entering a

Table 1.3 Dollar invoicing probability by product differentiation

	(1) Homog. (Rauch)	(2) Diff. (Rauch)	(3) Low diff. (CCHS)	(4) High diff. (CCHS)
UK competitors' dollar invoicing share	0.198**	0.075***	0.091***	0.043***
	(0.092)	(0.004)	(0.005)	(0.006)
Dollar import share	0.102***	0.164***	0.150***	0.182***
	(0.011)	(0.000)	(0.001)	(0.001)
Euro import share	-0.015	-0.009***	-0.010***	-0.010***
	(0.035)	(0.001)	(0.001)	(0.002)
Destination currency import share	0.081***	-0.019***	-0.011***	-0.029***
	(0.030)	(0.001)	(0.002)	(0.002)
Firm size	0.007***	0.016***	0.017***	0.015***
	(0.001)	(0.000)	(0.000)	(0.000)
Observations	10,663	4,708,964	2,611,076	1,883,102
Country-Year FE	✓	✓	✓	✓
Product-Year FE	✓	✓	✓	✓
Hansen J-stat	0.179	0.154	0.245	0.0368
[p-value]	[0.672]	[0.695]	[0.621]	[0.848]
Weak IV F-stat	89	69,553	35,952	29,562

Notes: The dependent variable is the dollar invoicing probability at the firm-product-destination-year level. All the results are based on 2SLS. Columns 1 and 2 are the results from the sub-samples for "traded on organized exchange" ('Homog') and "differentiated goods" ('Diff') based on Rauch (1999), respectively. Columns 3 to 4 are the results from the sub-samples according to the differentiation measure of Corsetti, Crowley, Han and Song (2018) in which 'Low diff.' denotes less differentiated goods and 'High diff.' denotes highly differentiated goods. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Fig. 1.7 Impact of dollar invoicing experience on dollar invoicing in new markets



Notes: The figure plots the trajectory of the coefficients of dummies for the number of previous dollar invoicing years (column 3, table 1.4). Top and bottom horizontal bars around each point estimate represent 90% confidence intervals. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

new destination are less prone to invoicing in local currency even when they use that currency for invoicing a share of their imports. In this case, they are more inclined to choose dollars for their initial transactions in the new destination.

Turning to the role of historical dollar-invoicing, the sixth row of column 1 indicates that a ten percentage point rise in a firm's previous dollar invoicing share is associated with a 2.9 percentage point increase in the probability of dollar invoicing in a new destination. Similarly, the seventh row of column 2 shows that firms with one additional year of dollar invoicing experience, prior to entry, are 2.5 percentage points more likely to choose dollars in their new destinations. Column 3 experiments with a full set of dummies indicating the specific number of years a firm has used dollars prior to entry – from one to six years (the excluded category is firms with no prior experience with dollar-invoicing). We again find a strictly monotonic relationship between a firm's previous dollar invoicing experience and its probability of choosing dollars for invoicing in new markets.

One might be concerned that these results could be driven simply by a positive association between firms' dollar invoicing years and their exporting tenure (as in figure 1.2). To address

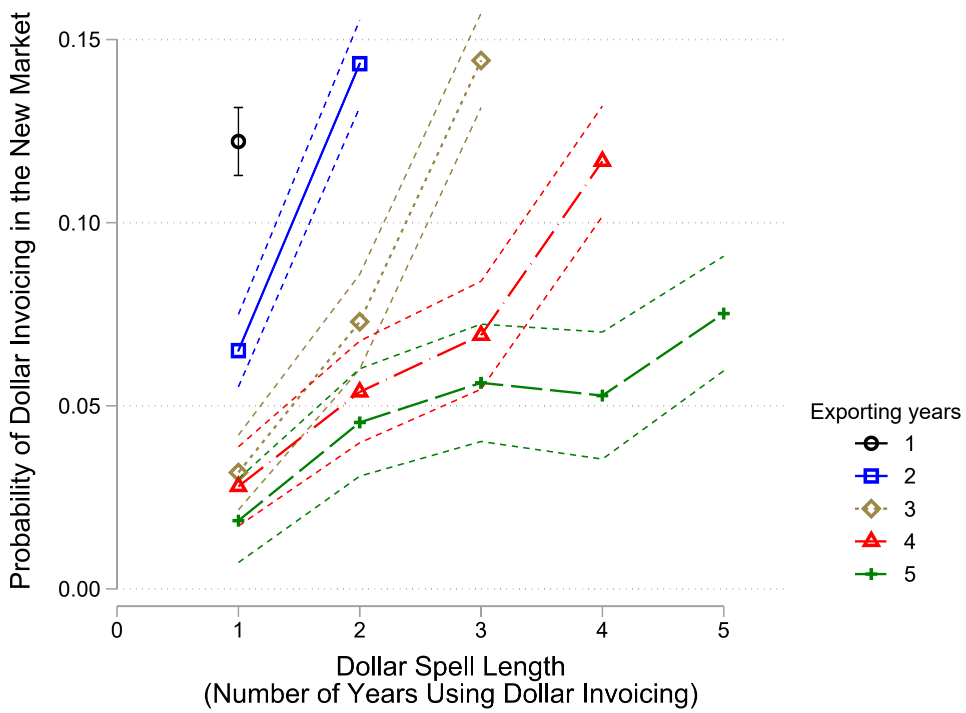
Table 1.4 Dollar invoicing probability at entry year

	(1)	(2)	(3)
UK competitors' dollar invoicing share	0.069***	0.071***	0.071***
	(0.007)	(0.007)	(0.007)
Dollar import share	0.093***	0.103***	0.103***
	(0.001)	(0.001)	(0.001)
Euro import share	-0.014***	-0.017***	-0.017***
	(0.002)	(0.002)	(0.002)
Destination currency import share	0.022***	0.014***	0.015***
	(0.002)	(0.002)	(0.002)
Firm size	0.013***	0.013***	0.013***
	(0.000)	(0.000)	(0.000)
Dollar share in total export (t-1)	0.292***		
	(0.002)		
Dollar invoicing years (t-1)		0.025***	
		(0.000)	
Dollar invoicing years (t-1) = 1			0.039***
			(0.001)
Dollar invoicing years (t-1) = 2			0.060***
			(0.002)
Dollar invoicing years (t-1) = 3			0.082***
			(0.002)
Dollar invoicing years (t-1) = 4			0.097***
			(0.003)
Dollar invoicing years (t-1) = 5			0.116***
			(0.004)
Dollar invoicing years (t-1) = 6			0.140***
			(0.005)
Observations	1,181,074	1,181,074	1,181,074
Country-Year FE	✓	✓	✓
Product-Year FE	✓	✓	✓
Hansen J-stat [p-value]	0.020 [0.886]	0.009 [0.922]	0.008 [0.926]
Weak IV F-stat	15,143	15,143	15,142

Notes: The dependent variable is the dollar invoicing probability at the firm-product-destination-year level. Observations are of the first-year of exporting in each firm-destination pair. All results are based on 2SLS. Robust standard errors in parentheses. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

this concern, we test an additional layer of heterogeneity, i.e., whether the effect of previous dollar invoicing on dollar invoicing in a new destination depends on a firm's export tenure. We introduce a full set of interaction terms between dummies for years of dollar-invoicing and dummies for the years of exporting. Figure 1.8 displays the trajectories of dollar-invoicing by exporting-year cohort. A key finding is that, across all exporting-year cohorts, the probability of dollar-invoicing in a new destination rises with previous dollar experience. It is worth noting that the marginal impact of additional experience becomes smaller for older exporters, as shown in the flatter trajectories for cohorts with longer export tenure.[30]

Fig. 1.8 Impact of dollar invoicing years by exporting year cohort



Notes: The figure plots the trajectories of the coefficients on dummies for the number of previous dollar invoicing years by each exporting year cohort. Dotted lines are 90% confidence intervals. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

What is interesting about the estimates in figures 1.7 and 1.8 is that the impact of previous dollar invoicing experience intensifies with the number of years beyond the first year. This means that the simple 'fixed' component of the cost of using a new currency alone is not sufficient to generate this empirical pattern. While it is true that the one-off fixed cost of adopting dollars would imply that the probability of dollar-invoicing in a new destination is higher for existing dollar users, it cannot generate the further dynamics of dollar invoicing

[30] Additionally, we break down our sample by firms' total export size in the last period before entry and estimate the specification in column 3 from table 1.4 for each sub-sample. As reported in appendix table 1.B3, the influence of the number of years of dollar-invoicing on dollar-invoicing in a new destination is less pronounced for large exporters compared to medium and small exporters.

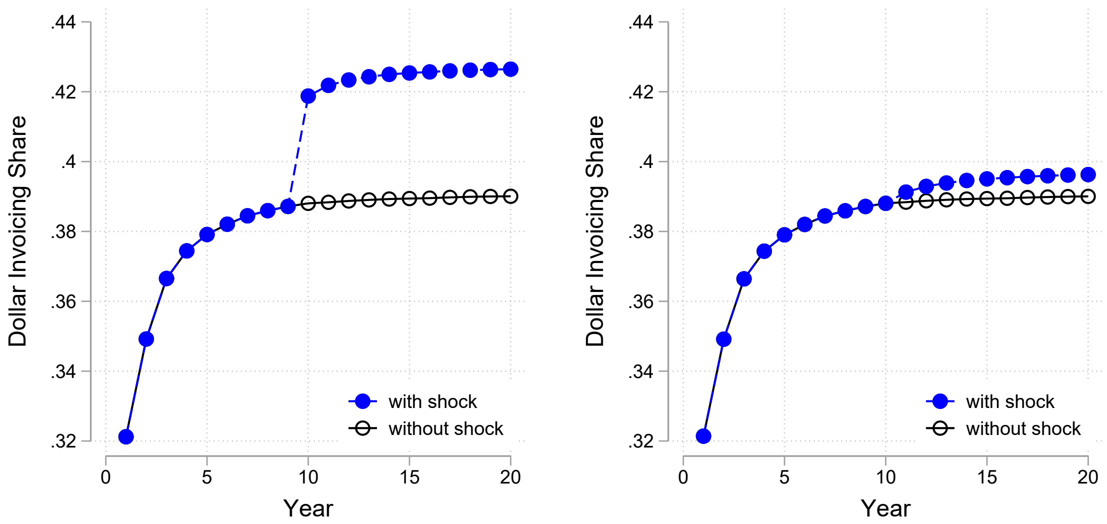
beyond the first year. That is, once the fixed cost is paid, any later years of dollar usage should not matter, contradictory to what is documented in figures 1.7 and 1.8.

1.6 Aggregate implications

To quantify the aggregate importance of the empirical channels driving currency choices, we conduct a partial equilibrium analysis. In particular, we study the effect of the positive feedback of prior dollar invoicing in the propagation of shocks and in sustaining a high dollar invoicing share.

Fig. 1.9 Propagation of destination-specific shocks

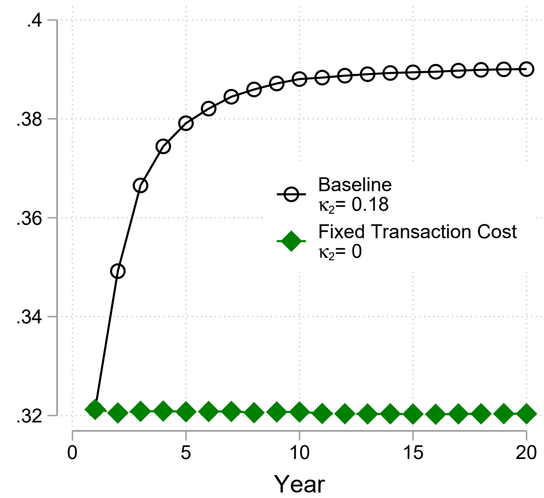
(a) All destinations (b) Non-shocked destinations



Notes: These two figures show the evolution of the aggregate dollar invoicing share in the simulated model with reduced form managerial costs of 200,000 firms, 20 destinations and 20 years. The left figure compares the dollar invoicing share for all destinations (black circles) versus the same statistic in a counterfactual environment where a destination-specific shock to the profitability of dollar invoicing was given in destination 1 at year 10 (blue dots). The right figure compares the dollar invoicing share for those other destinations (2-20) not hit by the shock.

We first investigate how a destination-specific shock propagates and affects the dollar-invoicing choices in other destinations not hit by the shock. We simulate the model for 20 years. For the first 10 periods, the model reaches its steady state. We then introduce a positive

Fig. 1.10 Evolution of aggregate dollar invoicing share with and without cost dynamics



Notes: This figure shows the evolution of the aggregate dollar invoicing share in two distinct versions of the simulated model. The black dots represent the aggregate dollar invoicing shares from the reduced form managerial cost model with positive feedback from prior dollar invoicing, i.e., $F(\omega^{\text{USD}}_{ft-1}) = \kappa_1 - \kappa_2 \omega^{\text{USD}}_{ft-1}$ and $\kappa_1 = 0.6$, whereas the blue squares represent evolution in per transaction managerial cost model without positive feedback, i.e., $F = \kappa_1$.

permanent shock to the profitability of using dollars in destination 1 at year 10.[31] Figure 1.9 shows the path of the aggregate dollar invoicing share across all destinations over time (left) and that for other destinations not hit by the shock (right). An immediate effect is an increase in the dollar-invoicing share in destination 1 as firms switch to dollar invoicing in response to the shock. This, in turn, increases the firms' overall dollar-invoicing share and thus the probability of dollar invoicing when entering other destinations. As a result, figure 1.9(b) shows that the dollar invoicing share in all other destinations rises gradually over time.

We conclude with an investigation of the role of dollar invoicing dynamics in sustaining a high dollar-invoicing share. Figure 1.10 shows the evolution of aggregate dollar-invoicing shares across all destinations. The model without the positive feedback from prior dollar use suggests that the dollar invoicing share would be 18% [(0.39-0.32)/0.39] lower compared to the model with the positive feedback.

[31] This captures events such as a destination country suddenly pegging its own currency to the dollar or forming a currency union. This could strengthen the exporters' incentives to invoice in dollars through, say, strategic complementarity.

1.7 Conclusions

A key feature of today's global macroeconomic environment is the dominance of the US dollar in the world's trade transactions. Since import prices tend to be stable in the currency of invoicing, the outsized role of the dollar in global trade has important implications for firms' responses to international and country-specific shocks, shedding light on the transmission of economic shocks internationally. Despite the importance of dollar dominance, there is little empirical evidence on the underlying mechanisms driving and sustaining the high dollar-invoicing share in global trade.

Using transaction level data on UK exports to extra-EU destinations, we document evidence on two key channels behind the dominance of the dollar. First, we find strong evidence of strategic complementarity in currency choices: UK exporters are more likely to use dollars if more UK competitors use dollars in the destination. This strategic motive is stronger for firms with larger market shares and for those selling less differentiated goods. Second, we document a significant role played by prior experience: firms entering a new destination are more likely to adopt dollars if they have used dollars more intensively and persistently in their existing markets.

We argue that the strategic complementarity and prior experience channels reinforce each other to sustain dollar dominance in international trade. Attentiveness to strategic complementarity seems to lead UK exporters to choose the US dollar in those foreign markets such as the US or Canada where the dollar dominates. Once a firm initiates dollar-invoicing for strategic reasons, a successful experience with dollar-invoicing in one market can propagate forward in time to the firm's other foreign markets, raising the share of dollar-invoicing to widely-dispersed locations.

We extend the standard theoretical framework of invoicing currency choice by introducing simple dynamics via the managerial cost of adopting an additional currency. Despite its simplicity, the structure we employ can successfully match the empirically documented firm-level dynamics of dollar invoicing. Counterfactual analysis of the model suggests the prior experience channel plays an important role in the propagation of destination-specific shocks and sustaining the high share of the US dollar in invoicing global trade.

Appendix 1.A Theoretical appendix

This appendix provides a detailed description of our conceptual framework that incorporates oligopolistic competition and a firm's use of multiple imported inputs into a model of currency choice under nominal rigidities. We further allow for the presence of a managerial cost that varies with the firm's prior dollar invoicing experience.

1.A.1 Production with multiple imported inputs

A firm uses labour and imported intermediate inputs to produce its output in the following production function

$$Y_f = A_f L_f^{1-\phi_f} \prod_{j=1}^{J} (M_{fj}^{\alpha_{fj}})^{\phi_f} \tag{1.A1}$$

where Y_f denotes output, A_f is the exogenously given firm productivity, L_f is labour and M_{fj} is imports of intermediates in currency j. Constant returns to scale imply $\sum_{j=1}^{J} \alpha_{fj} = 1$. J denotes the set of currencies in which intermediate inputs are invoiced. The firm's total production cost is expressed as

$$TC_f = WL_f + \sum_{j=1}^{J} \xi_{fj} P_{mj} M_{fj} \tag{1.A2}$$

where W is the nominal wage and P_{mj} is the price of foreign intermediate inputs invoiced in currency j. ξ_j is the nominal exchange rate expressed in units of producer currency per one unit of origin currency j. Cost minimization over labour and each intermediate input for a given level of output yields marginal cost as

$$MC_f = \frac{W^{1-\phi_f} P_M^{\phi_f}}{{A_f}^*} \tag{1.A3}$$

where ${A_f}^* = (1-\phi_f)^{1-\phi_f} {\phi_f}^{\phi_f} A_f$ and $P_M = \prod_{j=1}^{J_f} (\frac{\xi_{fj} P_{mj}}{\alpha_{fj}})^{\alpha_{fj}}$ is the price index of the intermediate input bundle. The share of imported inputs invoiced in currency j in the firm f's production cost, denoted by ψ_f^j, is equal to $\phi_f \alpha_{fj}$.

1.A.2 Optimal flexible price under oligopolistic competition

Firms entering a new destination d face a market structure featuring oligopolistic competition à la Atkeson and Burstein (2008) and Amiti, Itskhoki and Konings (2019). Each firm

f produces a differentiated good in each industry and exports it to destination market d. Consumers in each destination have a nested CES (constant elasticity of substitution) demand over the varieties of goods. The elasticity of substitution within and across industries are ρ and η, respectively, with $\rho > \eta \geq 1$. The demand faced by a firm f in destination d is

$$Q_{id} = P_{fd}^{-\rho} P_d^{\eta-\rho} D_d \tag{1.A4}$$

where D_d is the exogenous demand shifter, P_{fd} is the firm f's price in local currency and $P_d \equiv \left(\sum_f P_{fd}^{1-\rho}\right)^{\frac{1}{1-\rho}}$ is the aggregate price index in the destination. The effective demand elasticity is a function of the market share of the firm with large firms having a less elastic demand, i.e.,

$$\varepsilon_{fd} \equiv -\frac{d\log(Q_{fd})}{d\log(P_{fd})} = \rho(1-S_{fd}) + \eta S_{fd} \tag{1.A5}$$

where $S_{fd} \equiv \frac{P_{fd}Q_{fd}}{\sum_f P_{fd}Q_{fd}} = \left(\frac{P_{fd}}{P_d}\right)^{1-\rho}$ is the firm's destination-specific market share. If the firm is able to set its price flexibly in response to exchange rate shocks, its profit-maximizing price in local currency in the new destination d is

$$P_{fd} = \frac{\varepsilon(S_{fd})}{\varepsilon(S_{fd})-1}\frac{MC_f}{\xi_d}. \tag{1.A6}$$

Note that, unlike in monopolistic competition, the multiplicative markup ($\frac{\varepsilon_{fd}}{\varepsilon_{fd}-1}$) depends on the market share of individual firms (S_{fd}). The markup elasticity with respect to prices Γ_{fd} is expressed as

$$\Gamma_{fd} \equiv -\frac{d\log\left(\frac{\varepsilon_{fd}}{\varepsilon_{fd}-1}\right)}{d\log(P_{fd})} = \frac{(\rho-\eta)(\rho-1)S_{fd}(1-S_{fd})}{(\rho-(\rho-\eta)S_{fd})(\rho-1-(\rho-\eta)S_{fd})} \tag{1.A7}$$

Assuming that exchange rate movements are the only source of uncertainty, we can obtain the expression for the log of the optimal price p_{fd} by a first-order approximation of (1.A6) around the non-stochastic steady-state

$$p_{fd} \approx \frac{\Gamma_{fd}}{1+\Gamma_{fd}} p_{-fd} + \frac{1}{1+\Gamma_{fd}}\left(\sum_j^J \psi_f^j e_j - e_d\right) + \overline{C_{fd}} \tag{1.A8}$$

which is (1.4) in the text.

1.A.3 Optimal currency choice under nominal rigidities

To solve the problem (1.5), we adopt the lemma established in Engel (2006), Gopinath, Itskhoki and Rigobon (2010) and Mukhin (2018):

$$\bar{p}_{fd}^{c} = \mathbb{E}\left[p_{fd} + e_{d}^{c}\right]. \tag{1.A9}$$

This lemma indicates that the firm's optimal preset price $\bar{p}_{fd}^{c}$ is equal to the *expected* value of the optimal flexible price in invoicing currency c. An important implication of this is that the invoicing currency is relevant only if the firm considers the second-order moment of its expected profits. If the firm maximizes its expected profit up to the first-order approximation, the choice of invoicing currency is irrelevant as all the invoicing currencies yield the same expected value of *ex-post* price, $\mathbb{E}[\bar{p}_{fd}^{c} - e_{d}^{c}]$, which is simply the “average" of optimal price $\mathbb{E}\left[p_{fd}\right]$. Instead, if the firm targets up to the second-order moment of its expected profit, the invoicing currency helps to bring the *ex post* price $(\bar{p}_{fd}^{c} - e_{d}^{c})$ closer to its actual optimal flexible price (p_{fd}) contingent on any exchange rate movements.

With lemma (1.A9), the currency choice problem can be written as[32]

$$\max_{c} \mathbb{E}\left\{ \pi_{fd}(p_{fd}) + \frac{\partial^2 \pi_{fd}}{\partial p^2}|_{p=p_{fd}} (\bar{p}_{fd}^{c} - e_{d}^{c} - p_{fd})^2 - F_{f}^{c} \right\} \tag{1.A10}$$

$$\Leftrightarrow \max_{c} \left\{ \frac{\partial^2 \pi_{fd}}{\partial p^2}|_{p=\widetilde{p}_{fd}} * \mathrm{Var}[p_{fd} + e_{d} - e_{c}] - F_{f}^{c} \right\} \tag{1.A11}$$

where $\widetilde{p}_{fd}$ is the deterministic steady-state value of optimal price p_{fd}. $c = o, d, v, u$ corresponds to producer currency invoicing (PCI), local currency invoicing (LCI) and invoicing in the US dollar as a vehicle currency (VCI) and invoicing in euros as a vehicle currency (VCI2), respectively.[33] The optimal invoicing problem is therefore to choose currency c in which the variance of the optimal price plus the managerial cost F_{f}^{c} of adopting the currency are jointly *minimized*.

While simpler than before, the problem (1.A11) is still complicated. Specifically, as the firm chooses over multiple currencies, it considers various elements of exchange rate volatility in each currency ($\mathrm{Var}(e_{d})$, $\mathrm{Var}(e_{v})$, $\mathrm{Var}(e_{u})$) and the covariances for each pair of currencies

[32] The transformation from (1.A10) to (1.A11) involves the following two steps; First, as in Mukhin (2018), we assume $\frac{\partial^2 \pi_{fd}}{\partial p^2}|_{p=p_{fd}} = \frac{\partial^2 \pi_{fd}}{\partial p^2}|_{p=\widetilde{p}_{fd}} < 0$ to the zero-order approximation. Second, it holds that $\mathbb{E}[(\bar{p}_{fd}^{c} - e_{d}^{c}) - p_{fd}]^2 = \mathbb{E}[\mathbb{E}(p_{fd} + e_{d}^{c}) - (p_{fd} + e_{d}^{c})]^2 = \mathrm{Var}[p_{fd} + e_{d}^{c}] = \mathrm{Var}[p_{fd} + e_{d} - e_{c}]$.

[33] For convenience, we introduce a separate notation o for the choice of sterling, or producer currency invoicing (PCI). Note that $e_{d}^{o} = e_{d}$ and $e_{o} = 0$.

(Cov($e_d e_v$), Cov($e_d e_u$), Cov($e_v e_u$)).[34] To limit our attention to the three key determinants – strategic complementarity, imported inputs and managerial cost –, we introduce a set of simplifying assumptions:

- Similarly to Goldberg and Tille (2008), the log exchange rate is shaped by the differential of independent country-specific shocks; $e_c = \varsigma_o - \varsigma_c$, $e_c^{c'} \equiv e_c - e_{c'} = \varsigma_{c'} - \varsigma_c$ with a zero mean ($\mathbb{E}(\varsigma_o) = \mathbb{E}(\varsigma_c) = 0$) and an identical variance ($\sigma_o^2 = \sigma_c^2 = \sigma^2$) where ς_o denotes the home country shock. Then, $\mathbb{E}(e_c^2) = 2\sigma^2$ and $\mathbb{E}(e_c e_{c' \neq c}) = \sigma^2$ for any c and c'.[35]

- Again following Goldberg and Tille (2008), we express the log price index of firm f's competitors in destination d that is pertinent to the currency choice problem as[36]

$$p_{-fd} = -\sum_c \zeta_{(-f)d}^c (e_d - e_c) \tag{1.A12}$$

  where $\zeta_{(-f)d}^c$ denotes the total market share of the competitors which are invoicing in currency c in destination d, which satisfies $\sum_c \zeta_{(-f)d}^c = 1$. In our partial equilibrium setting, we assume these competitors' average invoicing shares as exogenously given.

- The set of currencies used for imported inputs is identical to that of export currencies: $J = \{o, d, v, u\}$.

Now we can derive the expected profit differences for each pair of currencies. Plugging the equations (1.A8) and (1.A12) into the variance expression (1.A11) and applying the

[34] Novy (2006) explores how the variances of each currency and covariances would affect the currency choice in a three-currency environment.

[35] We initially assume the exchange rate as $\xi_c = \overline{\xi} * \exp(e_c)$ where $\overline{\xi}$ is the steady-state exchange rate and e_c is a mean zero innovation. To simplify, let $\overline{\xi} = 1$ and thus $\log \xi_c = e_c$.

[36] This is due to our assumption that exchange rates are the only stochastic elements.

above set of simplifying assumptions yields the variance term as:

$$
\begin{aligned}
&\text{Var}[p_{fd}+e_d-e_c] \\
&= \text{Var}\Bigg[\frac{\Gamma_{fd}}{1+\Gamma_{fd}}(-\zeta^d_{(-f)d}e_d-\zeta^v_{(-f)d}e_d+\zeta^v_{(-f)d}e_v-\zeta^u_{(-f)d}e_d+\zeta^u_{(-f)d}e_u+e_d) \\
&\quad +\frac{1}{1+\Gamma_d}\sum_j^J \psi_j e_j - e_c\Bigg] \\
&= \text{Var}\left[\frac{\Gamma_{fd}}{1+\Gamma_{fd}}(\zeta^d_{(-f)d}e_d+\zeta^v_{(-f)d}e_v+\zeta^u_{(-f)d}e_u)+\frac{1}{1+\Gamma_{fd}}\sum_j^J \psi_{fj}e_j-e_c\right] \\
&= -\frac{2\Gamma_{fd}}{1+\Gamma_{fd}}(\zeta^d_{(-f)d}\mathbb{E}(e_de_c)+\zeta^v_{(-f)d}\mathbb{E}(e_ve_c)+\zeta^u_{(-f)d}\mathbb{E}(e_ue_c)) \\
&\quad -\frac{2}{1+\Gamma_{fd}}\sum_j^J \psi_{fj}\mathbb{E}(e_je_c)+\mathbb{E}(e_c^2)+..
\end{aligned}
$$

The third line uses $\sum_c \zeta^c_{(-f)d}=1$ and the fourth line displays only the terms involving e_c as all other terms will be cancelled out when differencing the variances across currencies. Then, for each pair of invoicing currencies,

$$
\begin{aligned}
&\textbf{(VCI vs PCI)}\quad \Delta_{v,o}\,\text{Var}_{fd} = -\left[\frac{2\sigma^2\Gamma_{fd}}{1+\Gamma_{fd}}(\zeta^v_{(-f)d}-\zeta^o_{(-f)d})+\frac{2\sigma^2}{1+\Gamma_{fd}}(\psi^v_f-\psi^o_f-1)\right] \\
&\textbf{(VCI vs LCI)}\quad \Delta_{v,d}\,\text{Var}_{fd} = -\left[\frac{2\sigma^2\Gamma_{fd}}{1+\Gamma_{fd}}(\zeta^v_{(-f)d}-\zeta^d_{(-f)d})+\frac{2\sigma^2}{1+\Gamma_{fd}}(\psi^v_f-\psi^d_f)\right] \\
&\textbf{(VCI vs VCI2)}\quad \Delta_{v,u}\,\text{Var}_{fd} = -\left[\frac{2\sigma^2\Gamma_{fd}}{1+\Gamma_{fd}}(\zeta^v_{(-f)d}-\zeta^u_{(-f)d})+\frac{2\sigma^2}{1+\Gamma_{fd}}(\psi^v_f-\psi^u_f)\right]
\end{aligned}
$$

where $\Delta_{v,b}\,\text{Var}_{fd} \equiv \text{Var}[p_{fd}+e_d-e_v]-\text{Var}[p_{fd}+e_d-e_b]$. The expected profit difference over currency v and b is summarized as

$$
\mathbb{E}[\Pi^v_{fd}]-\mathbb{E}[\Pi^b_{fd}] \propto \lambda_{fd}\Bigg[\underbrace{\frac{\Gamma_{fd}}{1+\Gamma_{fd}}(\zeta^v_{(-f)d}-\zeta^b_{(-f)d})}_{\text{Strategic complementarity}}+\underbrace{\frac{1}{1+\Gamma_{fd}}(\psi^v_f-\psi^b_f)}_{\text{Operational hedging}}\Bigg]-\underbrace{(F^v_f-F^b_f)}_{\text{Managerial cost}}
$$

where $\lambda_{fd} \equiv -2\sigma^2\frac{\partial^2\pi_{fd}}{\partial p^2}|_{p=\widetilde{p}_{fd}}>0$. The likelihood of choosing currency v relative to any other arbitrary currency b increases with the difference of the expected profits in the last equation.

1.A.4 A general framework for invoicing dynamics

In this section, we discuss a general framework of invoicing currency dynamics. We start by considering a transition function $T(.)$ that maps a firm's dollar invoicing share ω_{ft-1}^{USD} into the probability of dollar invoicing when a new destination is added. That is, when the dollar invoicing share of firm f takes the value of x, the probability of choosing dollar invoicing in a new destination d in period t is given by $T(x)$:

$$T(x) \equiv Pr(\mathbb{1}_{fdt}^{\text{USD}} = 1 | \omega_{ft-1}^{USD} = x) \tag{1.A13}$$

In principle, the exact functional form of $T(x)$ can depend on the distribution of a bunch of factors, such as share of dollar invoicing competitors and the dollar share of imported inputs predicted by a conventional static model. We abstract from the exact functional form of (1.A13) for the moment and focus on discussing the general properties of $T(x)$ and its relationship with the key variable of our interest, the dollar spell length, $Spell_{ft}^{USD}$.

Using the transition function (1.A13), it can be shown that the dollar invoicing probability in a new destination conditional on a specific dollar spell length depends on two elements: (1) the distribution of dollar invoicing shares conditional on the dollar spell length[37] and (2) the transition function $T(x)$. More specifically, the conditional probability of dollar invoicing in a new destination for a firm with dollar spell length l can be written as:

$$\begin{aligned} Pr(\mathbb{1}_{fdt}^{\text{USD}} = 1 | Spell_{ft-1}^{USD} = l) &= \sum_x Pr(\omega_{ft-1}^{USD} = x | Spell_{ft-1}^{USD} = l) T(x) \\ &= \frac{\sum_x Pr(\omega_{ft-1}^{USD} = x \bigcap Spell_{ft-1}^{USD} = l) T(x)}{\sum_x Pr(\omega_{ft-1}^{USD} = x \bigcap Spell_{ft-1}^{USD} = l)} \end{aligned} \tag{1.A14}$$

If the transition function $T(.)$ does not depend on the dollar share, then the probability of using dollar invoicing in the new destination is independent of the dollar spell length, i.e., $Pr(\mathbb{1}_{it}^{\text{USD}} = 1 | Spell_{it-1}^{USD} = l)$ is a constant for all l.[38]

To further characterize the dynamics of invoicing currency choices, we specify on how firms grow by extending their markets and how these firms make invoicing choices in their

[37] For example, given a firm has used dollar invoicing for two years, $Spell_{ft-1}^{USD} = 2$, what is the probability that its dollar invoicing share is x, e.g., $x = 0, 0.5, 1$, etc.

[38] It is worth stressing that this result does not depend on the dynamic process of firm distributions. An important case in which $T(.)$ does not depend on the dollar share is when the dollar invoicing probability in a new destination is firm-specific but time invariant, e.g., firms that need to constantly import lots of dollar invoiced inputs are more likely to invoice their exports in dollars. Therefore, this property rules out this case as a possible explanation for the empirical facts documented in figures 1.7 and 1.8.

existing and new markets. Specifically, to keep the model tractable, we make the two simplifying assumptions as following:

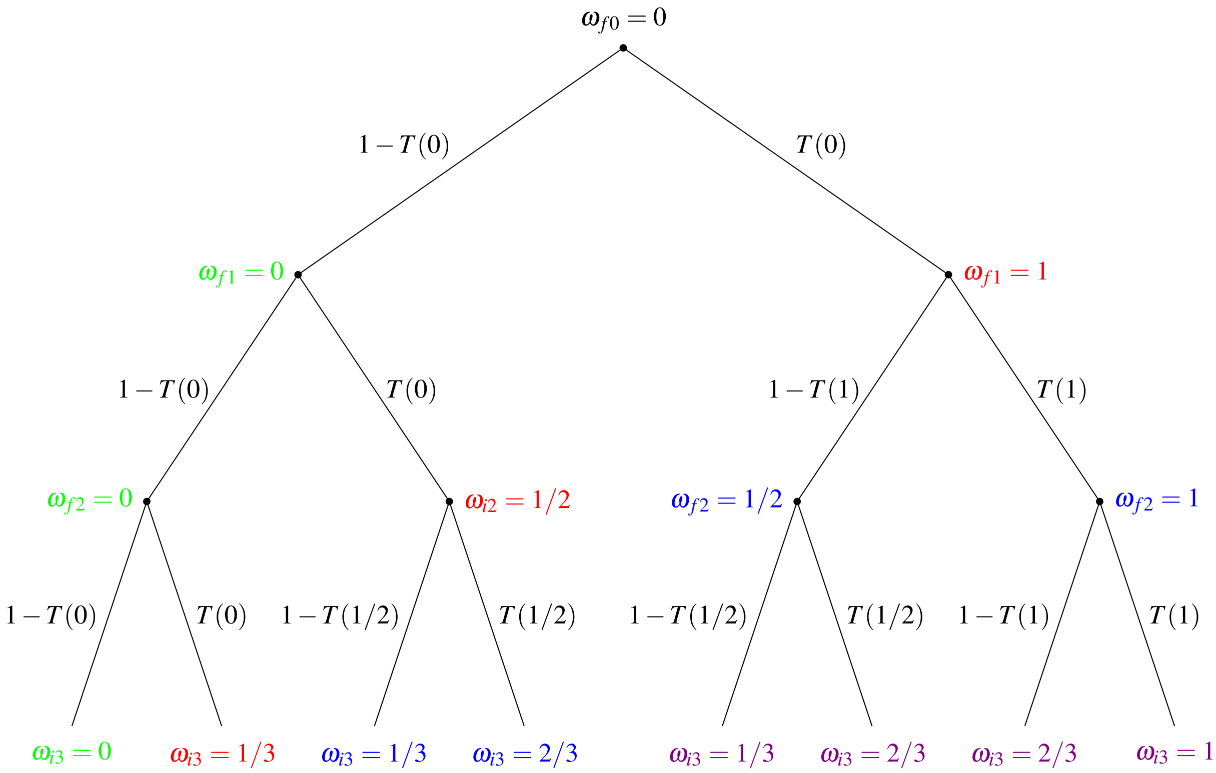
(1) A firm enters a new market in each period and the size of each market is normalized to one in all periods

(2) A firm sticks to the currency selected upon entry for each of its existing markets.[39]

Figure 1.A1 illustrates the evolution of the dollar spell and dollar invoicing share for the first 3 periods. In the initial period $t = 0$, all firms start with zero foreign markets and therefore a zero dollar invoicing share. In period 1, each firm enters one foreign market. For a given transition function $T(x)$, the probability of dollar invoicing in the foreign market is $T(0)$. As shown in figure 1.A1, there is a probability of $T(0)$ that the firm chooses to invoice in dollars and has a dollar export share of $\omega_{f1} = 1$ and $1 - T(0)$ probability of invoicing in other currencies with a dollar trade share of $\omega_{f1} = 0$. In period 2, each firm adds one more new destination and the dollar invoicing share will change according to the existing dollar share ω_{f1} and the transition function $T(\omega_{f1})$. As illustrated in the third row of figure 1.A1, there is a probability $[1 - T(0)]^2$ that the firm does not use dollars in any of the two markets in period 2 and has a dollar spell of zero (i.e., $Spell_{f2}^{USD} = 0$). With probability $[1 - T(0)]T(0)$, the firm uses dollar in the newly added market and has a dollar spell of one, i.e., $Spell_{f2}^{USD} = 1$. There is a probability $T(0)[1 - T(1)]$ that the firm uses dollar only in the previously added markets and a probability $[T(1)]^2$ that the firm uses dollars in both markets. In both cases, the firm has a dollar spell of two, i.e., $Spell_{f2}^{USD} = 2$. The distributions of the dollar invoicing choices and the dollar spell in later periods can be obtained by continutously iterating the process outlined in figure 1.A1.

[39]We add this assumption for the sake of analytical convenience. Removing this assumption will strengthen the mechanism. We discuss the spillover effect of the invoicing choices in the new destination on existing destinations in the next subsection.

Fig. 1.A1 Illustrating the relationship between dollar spell and dollar invoicing share



Notes: This figure shows the evolution of the dollar spell and the dollar invoicing share of a firm beginning to export under the following three assumptions: (1) the firm enters one new market in each period and (2) the firm sticks to the invoicing currency of its initial choice for the existing markets. $T(x)$ represents the probability of invoicing in dollar in a new destination given the dollar invoicing share at the firm level. ω_{ft} represents the firm's dollar invoicing share in period t, where $t = 0, 1, 2, 3$. Different colors highlight positions identified with different dollar spell lengths. Green, red, blue and violet indicate a dollar spell length of zero, one, two and three years, respectively.

The key challenge, as can be seen in figure 1.A1, is to characterize the relationship between firms' dollar spell lengths and the distribution of dollar invoicing shares. The tricky part is that the dollar invoicing share, the key variable in the transition function, is only indirectly linked to the dollar spell length. A firm is characterized as a dollar user (and therefore the dollar spell length will be increased by 1 year) if the firm used dollars at least once in any of its export destinations previously. Therefore, for a given dollar spell length, the dollar invoicing share can differ substantially across firms. Under our assumption 1, the dollar invoicing probability in a new destination conditional on the spell length $Spell^{USD}_{ft-1}$ and the exporting age of the firm age_t depends on the distribution of dollar invoicing in the last period (i.e., the values of ω_{ft-1}) and the transition function $T(x)$. With assumption 2, the conditional probability of dollar invoicing in a new destination can be solved explicitly and is given by[40]

$$Pr(\mathbb{1}_{fdt}^{\text{USD}} = 1 | Spell_{ft-1}^{USD} = 0 \bigcap age_{ft} = \tau) = T(0) \tag{1.A15}$$

$$Pr(\mathbb{1}_{fdt}^{\text{USD}} = 1 | Spell_{ft-1}^{USD} = 1 \bigcap age_{ft} = \tau) = T\left(\frac{1}{\tau}\right) \tag{1.A16}$$

$$Pr(\mathbb{1}_{fdt}^{\text{USD}} = 1 | Spell_{ft-1}^{USD} = 2 \bigcap age_{ft} = \tau) = \left[1 - T\left(\frac{1}{\tau-1}\right)\right] T\left(\frac{1}{\tau}\right) + T\left(\frac{1}{\tau-1}\right) T\left(\frac{2}{\tau}\right) \tag{1.A17}$$

As can be seen from equations (1.A15)-(1.A17), a sufficient condition to get our empirical results of dollar invoicing dynamics (i.e., figures 1.7 and 1.8) is that $T(x)$ is an increasing function of x.[41] An increasing transition function of $T(x)$ ensures a positive reinforcement loop as it means firms starting with a high dollar invoicing share are also more likely to use dollars in a new destination. This implies that firms with a dollar spell length of one year are more likely to use dollars in a new destination in the next period than those firms with a dollar spell length of zero; hence these firms are more likely to end up with high dollar shares which in turn increases the dollar invoicing probability in a new destination in the following period. Notably, the condition that $T(x)$ is an increasing function of x also naturally generates the pattern documented in figure 1.8. As shown in (1.A16) and (1.A17), for a given dollar spell length, the dollar invoicing probability in a new destination decreases in the exporting age of the firm τ.

[40] $Pr(\mathbb{1}_{fdt}^{\text{USD}} = 1 | Spell_{ft-1}^{USD} = 3 \bigcap age_t = \tau) = a_1(\tau) T\left(\frac{1}{\tau}\right) + a_2(\tau) T\left(\frac{2}{\tau}\right) + a_3(\tau) T\left(\frac{3}{\tau}\right)$ where $a_1(\tau) = [1 - T\left(\frac{1}{\tau-2}\right)][1 - T\left(\frac{1}{\tau-1}\right)]$; $a_2(\tau) = [1 - T\left(\frac{1}{\tau-2}\right)] T\left(\frac{1}{\tau-1}\right) + T(1)[1 - T(1)]$; $a_3(\tau) = T^2(1)$. More generally, when the total number of years is greater than 3, we have $a_1(\tau) = [1 - T\left(\frac{1}{\tau-2}\right)][1 - T\left(\frac{1}{\tau-1}\right)]$; $a_2(\tau) = [1 - T\left(\frac{1}{\tau-2}\right)] T\left(\frac{1}{\tau-1}\right) + T\left(\frac{1}{\tau-2}\right)[1 - T\left(\frac{2}{\tau-1}\right)]$; $a_3(\tau) = T\left(\frac{1}{\tau-2}\right) T\left(\frac{2}{\tau-1}\right)$.

[41] Given $T(x)$ is an increasing in x, it is straightforward to see the dollar invoicing probability in a new destination is higher for any firm age τ as the dollar spell length increases.

Appendix 1.B Further estimation results

Table 1.B1 Summary statistics of estimation sample

		Unweighted		Weighted	
	Obs	Mean	Std	Mean	Std
Dollar invoicing probability	4,719,628	0.229	0.420	0.362	0.480
Dollar import share	4,719,628	0.571	0.391	0.603	0.365
Euro import share	4,719,628	0.055	0.158	0.054	0.159
Destination currency import share	4,719,628	0.113	0.287	0.199	0.346
Firm size (log)	4,719,628	14.559	3.231	19.181	2.774
UK competitors' dollar invoicing share	4,719,628	0.254	0.285	0.359	0.336
UK competitor's dollar import share	4,719,628	0.578	0.246	0.594	0.272
UK competitors' firm size (log)	4,719,628	15.748	2.093	18.307	2.529

Notes: 'Weighted' indicates that the variables are weighted by export values at the firm-product-destination-year level. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Table 1.B2 First-stage regression for UK competitors' dollar invoicing share

UK competitors' dollar import share	0.202***
	(0.000)
UK competitors' firm size	0.013***
	(0.000)
Observations	4,719,628
Adjusted R^2	0.435
Country-Year FE	✓
Product-Year FE	✓

Notes: The first-stage regression for 2SLS in columns 4 from table 1.1. The dependent variable is UK competitors' dollar invoicing share at the firm-industry-destination-year level for which industry is defined at 6-digit level. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Table 1.B3 Dollar invoicing probability at entry year: By firm size in year t-1

	(1) Baseline	(2) 0-5p	(3) 5-25p	(4) 25-50p	(5) 50-75p	(6) 75-95p	(7) 95-100p
UK competitors' dollar invoicing share	0.071***	0.009	0.019	-0.000	0.048**	0.081***	0.075
	(0.007)	(0.055)	(0.024)	(0.023)	(0.022)	(0.024)	(0.054)
Dollar import share	0.103***	0.040***	0.042***	0.051***	0.087***	0.140***	0.218***
	(0.001)	(0.006)	(0.003)	(0.003)	(0.003)	(0.005)	(0.015)
Euro import share	-0.017***	0.017	-0.006	-0.019***	0.007	-0.047***	0.010
	(0.002)	(0.017)	(0.007)	(0.006)	(0.007)	(0.009)	(0.028)
Destination currency import share	0.015***	0.039**	0.053***	0.011	-0.018	-0.044*	0.008
	(0.002)	(0.015)	(0.009)	(0.011)	(0.016)	(0.027)	(0.134)
Firm size	0.013***	0.015***	0.009***	0.012***	0.009***	0.005***	0.016***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Dollar invoicing years (t-1) = 1	0.039***	0.122***	0.113***	0.093***	0.082***	0.076***	0.082***
	(0.001)	(0.011)	(0.004)	(0.003)	(0.003)	(0.005)	(0.020)
Dollar invoicing years (t-1) = 2	0.060***	0.103***	0.166***	0.134***	0.114***	0.099***	0.099***
	(0.002)	(0.022)	(0.007)	(0.004)	(0.004)	(0.006)	(0.023)
Dollar invoicing years (t-1) = 3	0.082***	0.209***	0.223***	0.168***	0.152***	0.125***	0.134***
	(0.002)	(0.040)	(0.011)	(0.006)	(0.005)	(0.007)	(0.025)
Dollar invoicing years (t-1) = 4	0.097***	0.168**	0.237***	0.199***	0.181***	0.167***	0.120***
	(0.003)	(0.068)	(0.016)	(0.009)	(0.006)	(0.008)	(0.030)
Dollar invoicing years (t-1) = 5	0.116***	0.138	0.328***	0.244***	0.193***	0.188***	0.095***
	(0.004)	(0.140)	(0.023)	(0.011)	(0.008)	(0.010)	(0.031)
Dollar invoicing years (t-1) = 6	0.140***	-	0.387***	0.251***	0.256***	0.212***	0.134***
	(0.005)	(-)	(0.041)	(0.015)	(0.010)	(0.011)	(0.035)
Observations	1,181,074	16,232	77,208	97,942	98,036	77,735	17,544
Country-Year FE	✓	✓	✓	✓	✓	✓	✓
Product-Year FE	✓	✓	✓	✓	✓	✓	✓
Hansen J-stat	0.008	0.073	6.431	0.004	2.036	0.024	0.429
[P-value]	[0.926]	[0.787]	[0.011]	[0.946]	[0.154]	[0.875]	[0.512]
Weak IV F-stat	15,142	225	1,122	1,471	1,545	1,448	298

Notes: The dependent variable is the dollar invoicing probability as the firm-product-destination-year level. Column 1 presents the baseline results from column 1 in table 1.4. Columns 2 to 7 show the results for sub-samples based on the firms' total export values in the previous year. '0-5p' indicates firms with previous export values less than the bottom five percentile in the sample and so on. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source:HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Appendix 1.C Distributional statistics on invoicing currency

Table 1.C1 Years of Exporting & Number of Invoicing Currencies

Years of Exporting	Number of Invoicing Currencies					Share using 2+ currencies
	1	2-5	6-10	10+	Total	given export experience
(a) by Share of Firm-Year Units						
1	26.1	5.5	0.1	0.0	31.7	17.6
2	14.6	5.4	0.1	0.0	20.1	27.4
3	9.9	4.8	0.1	0.0	14.9	32.9
4	7.1	4.4	0.1	0.0	11.6	38.8
5	5.1	4.0	0.1	0.0	9.2	44.6
6	3.6	3.5	0.1	0.0	7.2	50.0
7	2.3	3.0	0.1	0.0	5.4	57.4
Total	68.8	30.7	0.4	0.1	100.0	
(b) by Share of Trade Values						
1	1.8	7.9	2.1	1.6	13.5	86.7
2	1.4	8.2	2.7	1.8	14.2	90.1
3	1.1	8.4	2.4	2.3	14.2	92.3
4	1.0	8.0	3.1	1.7	13.8	92.7
5	0.7	10.2	2.0	2.2	15.1	95.4
6	0.4	9.6	2.8	2.6	15.5	97.4
7	0.5	7.8	2.9	2.6	13.8	96.4
Total	7.0	60.2	17.9	14.9	100.0	
(c) by Share of Transactions						
1	4.9	9.2	1.0	0.7	15.8	69.0
2	3.7	9.4	1.1	0.7	14.9	75.2
3	3.1	9.4	1.1	0.8	14.4	78.5
4	2.7	9.7	1.2	0.9	14.5	81.4
5	2.2	9.5	1.1	1.1	13.8	84.1
6	1.8	9.4	1.3	1.0	13.5	86.7
7	1.4	9.2	1.3	1.2	13.2	89.4
Total	19.7	65.7	8.1	6.5	100.0	

Notes: The raw data have five panel dimensions, namely firm, product, invoicing currency, origin/destination, and date. We aggregate data and calculate the dollar invoicing share at the firm-year level. To construct the table, we split the data into different bins as defined by the row and column categories. For stastistics in panel (a), we count the number of firm-years that fall into each bin. For stastistics in panels (b) and (c), we calculate the total trade value (denominated in sterling) and the number of annual transactions of firm-year units that fall into each bin. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Table 1.C2 Years of Exporting & Dollar Invoicing Share

Years of Exporting	Dollar Invoicing Share						Share with
	0	(0, 0.05]	(0.05, 0.15]	(0.15, 0.5]	(0.5, 1]	Total	dollar-invoicing> 0.5
(a) by Share of Firm-Year Units							
1	24.9	0.8	1.4	0.7	3.9	31.7	12.3
2	14.5	0.8	1.4	0.8	2.6	20.1	12.9
3	10.1	0.8	1.3	0.7	2.0	14.9	13.4
4	7.4	0.8	1.2	0.6	1.6	11.6	13.7
5	5.4	0.7	1.1	0.6	1.4	9.2	15.2
6	3.9	0.7	1.0	0.5	1.2	7.2	16.6
7	2.5	0.6	0.8	0.5	1.0	5.4	18.5
Total	68.7	5.2	8.1	4.4	13.6	100.0	
(b) by Share of Trade Values							
1	1.8	3.2	3.0	1.4	4.1	13.5	30.4
2	1.7	3.6	3.5	0.8	4.6	14.2	32.4
3	1.5	3.0	3.1	1.5	5.0	14.2	35.2
4	1.3	3.0	3.4	1.4	4.7	13.8	34.0
5	1.0	2.8	4.9	1.4	5.0	15.1	33.1
6	0.6	3.4	5.2	1.1	5.1	15.5	32.9
7	0.6	3.2	3.8	1.4	4.8	13.8	34.8
Total	8.5	22.2	26.9	9.0	33.4	100.0	
(c) by Share of Transactions							
1	5.4	2.4	3.7	1.5	2.8	15.8	17.7
2	4.3	2.4	3.7	1.6	2.9	14.9	19.5
3	3.7	2.3	3.4	1.7	3.3	14.4	22.9
4	3.3	2.5	3.9	1.7	3.1	14.5	21.4
5	2.7	2.5	3.8	1.7	3.2	13.8	23.2
6	2.3	2.5	3.8	1.6	3.3	13.5	24.4
7	1.8	2.3	3.9	1.8	3.3	13.2	25.0
Total	23.5	16.8	26.1	11.7	21.9	100.0	

Notes: The raw data have five panel dimensions, namely firm, product, invoicing currency, origin/destination, and date. We aggregate data and calculate the dollar invoicing share at the firm-year level. To construct the table, we split the data into different bins as defined by the row and column categories. For stastistics in panel (a), we count the number of firm-years that fall into each bin. For stastistics in panels (b) and (c), we calculate the total trade value (denominated in sterling) and the number of annual transactions of firm-year units that fall into each bin. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Table 1.C3 Prior Years of Dollar Invoicing vs. Dollar Invoicing Share

Prior Years of	Dollar Invoicing Share					
Dollar Invoicing	0	(0, 0.05]	(0.05, 0.15]	(0.15, 0.5]	(0.5, 1]	Total
(a) by Share of Firm-Year Units						
0	49.0	3.8	5.8	3.2	9.5	71.3
1	3.8	1.8	2.8	1.6	3.0	13.1
2	1.1	1.1	1.8	1.0	1.9	6.8
3	0.4	0.6	1.2	0.6	1.2	4.1
4	0.2	0.4	0.8	0.4	0.8	2.5
5	0.1	0.2	0.5	0.2	0.5	1.5
6	0.0	0.1	0.2	0.1	0.3	0.7
Total	54.7	7.9	13.2	7.0	17.2	100.0
(b) by Share of Trade Values						
0	8.0	20.5	24.7	8.2	31.6	93.1
1	0.3	0.7	0.7	0.4	1.0	3.0
2	0.1	0.4	0.3	0.3	0.4	1.4
3	0.0	0.4	1.0	0.1	0.2	1.7
4	0.0	0.1	0.2	0.1	0.1	0.4
5	0.0	0.0	0.1	0.0	0.1	0.2
6	0.0	0.1	0.0	0.0	0.0	0.1
Total	8.5	22.2	26.9	9.0	33.4	100.0
(c) by Share of Transactions						
0	21.7	14.3	22.0	9.5	18.1	85.6
1	1.3	1.2	2.0	1.1	1.7	7.4
2	0.3	0.7	0.9	0.5	0.9	3.4
3	0.1	0.3	0.5	0.3	0.6	1.8
4	0.0	0.2	0.3	0.2	0.3	1.0
5	0.0	0.1	0.2	0.1	0.2	0.6
6	0.0	0.0	0.1	0.0	0.1	0.3
Total	23.5	16.8	26.1	11.7	21.9	100.0

Notes: The raw data have five panel dimensions, namely firm, product, invoicing currency, origin/destination, and date. Prior years of dollar invoicing indicates the total number of years that each firm used invoiced in dollars up to $t-1$ and dollar invoicing share is measured at t. We aggregate data and calculate the dollar invoicing share at the firm-year level. To construct the table, we split the data into different bins as defined by the row and column categories. For stastistics in panel (a), we count the number of firm-years that fall into each bin. For stastistics in panels (b) and (c), we calculate the total trade value (denominated in sterling) and the number of annual transactions of firm-year units that fall into each bin. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Table 1.C4 Years of Exporting vs. Number of Exported Products

	Number of Exported Products				
Years of Exporting	1	2-5	6-10	10+	Total
(a) by Share of Firm-Year Units					
1	18.2	9.7	2.0	1.8	31.7
2	8.2	7.9	2.1	1.8	20.1
3	4.8	6.3	2.0	1.8	14.9
4	3.0	4.9	1.8	1.8	11.6
5	2.0	3.9	1.6	1.7	9.2
6	1.2	3.0	1.4	1.6	7.2
7	0.7	2.0	1.1	1.6	5.4
Total	38.1	37.8	11.9	12.2	100.0
(b) by Share of Trade Values					
1	0.8	2.1	1.2	9.4	13.5
2	0.4	1.7	1.3	10.8	14.2
3	0.3	1.4	1.7	10.7	14.2
4	0.4	1.4	1.2	10.8	13.8
5	0.2	1.2	1.4	12.3	15.1
6	0.1	1.0	1.1	13.3	15.5
7	0.1	0.8	1.1	11.8	13.8
Total	2.4	9.6	9.0	79.0	100.0
(c) by Share of Transactions					
1	1.6	2.9	2.0	9.2	15.8
2	0.8	2.6	2.2	9.3	14.9
3	0.5	2.2	2.1	9.6	14.4
4	0.3	1.9	2.0	10.2	14.5
5	0.2	1.6	1.8	10.2	13.8
6	0.2	1.4	1.7	10.3	13.5
7	0.1	1.0	1.4	10.6	13.2
Total	3.8	13.7	13.1	69.4	100.0

Notes: The raw data have five panel dimensions, namely firm, product, invoicing currency, origin/destination, and date. We aggregate data and calculate the number of products exported at the firm-year level. To construct the table, we split the data into different bins as defined by the row and column categories. For stastistics in panel (a), we count the number of firm-years that fall into each bin. For stastistics in panels (b) and (c), we calculate the total trade value (denominated in sterling) and the number of annual transactions of firm-year units that fall into each bin. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Table 1.C5 Years of Exporting vs. Number of Exporting Destinations

	Number of Exporting Destinations				
Years of Exporting	1	2-5	6-10	10+	Total
(a) by Share of Firm-Year Units					
1	21.1	7.9	1.5	1.2	31.7
2	10.1	7.1	1.5	1.3	20.1
3	6.1	5.9	1.5	1.3	14.9
4	3.9	4.8	1.5	1.3	11.6
5	2.6	3.9	1.4	1.3	9.2
6	1.6	3.1	1.3	1.3	7.2
7	0.8	2.2	1.1	1.2	5.4
Total	46.2	35.0	9.8	9.0	100.0
(b) by Share of Trade Values					
1	1.0	1.5	1.5	9.5	13.5
2	0.5	1.7	1.2	10.8	14.2
3	0.4	1.5	1.1	11.2	14.2
4	0.2	1.4	1.1	11.1	13.8
5	0.3	1.1	1.3	12.3	15.1
6	0.2	0.9	1.4	13.1	15.5
7	0.2	0.6	1.0	12.0	13.8
Total	2.8	8.7	8.5	80.1	100.0
(c) by Share of Transactions					
1	2.5	3.1	2.1	8.1	15.8
2	1.4	3.1	2.2	8.2	14.9
3	0.9	2.7	2.2	8.5	14.4
4	0.7	2.4	2.2	9.3	14.5
5	0.5	2.1	2.0	9.3	13.8
6	0.3	1.7	2.0	9.5	13.5
7	0.2	1.3	1.8	9.8	13.2
Total	6.4	16.5	14.4	62.7	100.0

Notes: The raw data have five panel dimensions, namely firm, product, invoicing currency, origin/destination, and date. We aggregate data and calculate the number of destinations at the firm-year level. To construct the table, we split the data into different bins as defined by the row and column categories. For stastistics in panel (a), we count the number of firm-years that fall into each bin. For stastistics in panels (b) and (c), we calculate the total trade value (denominated in sterling) and the number of annual transactions of firm-year units that fall into each bin. Data source: HMRC Overseas Trade in Goods Statistics, UK's extra-EU export transactions, 2010-2016.

Chapter 2

The vertical propagation of the US-China trade war

2.1 Introduction

Since the United States implemented unprecedented tariff increases against China in 2018, the US-China trade war has become a burgeoning area of research in terms of its economic impact and its broad implications for the world trading system (Crowley (2019)). Several studies thus far focus on the impact of these tariffs on US consumers and firms that are directly involved in the war.[1] However, an important aspect of modern international trade is the rapid expansion of globally interconnected supply chains and the rise in intermediates trade. And the vertical linkages across countries and sectors could potentially work as a channel through which a local trade shock could create substantial repercussions on third countries and global trade as a whole (Caliendo and Parro (2014)).

This paper investigates a spillover impact of the US-China tariff war on other countries through vertical linkages. The empirical analysis of this paper uses 29 countries' industry-level exports to China between 2017:Q1 and 2019:Q3 to examine the US-China tariff events that have taken place since 2018. Among several potential channels, I pay attention to the upstream propagation of US tariffs on Chinese imports into China's demand for foreign intermediates. This channel, which I refer to as the 'US vertical shock', is particularly relevant in light of the China's rise in global supply chains and the importance of the US markets

[1] To name a few, see Amiti, Redding and Weinstein (2019), Amiti, Redding and Weinstein (2020) and Fajgelbaum, Goldberg, Kennedy and Khandelwal (2019) for US consumers and welfare and Amiti, Kong and Weinstein (2020) and Handley, Kamal and Monarch (2020) for investment and exports of US firms.

for Chinese exporters.[2] A key feature of this analysis lies in building an industry-specific measure of input-output linkages with China for each country exporting to China. This measure is constructed using both the Chinese detailed input-output (IO) table and World IO tables together with the US tariff changes against China. Using this measure, I find strong and robust evidence that the massive US tariff hikes since 2018 led to a significant contraction of other countries' exports to China through input-output linkages. The economic magnitude is large. A one standard deviation rise in this vertical shock measure is associated with a decline in the growth rate of these countries' exports of intermediates towards China by 9.6 percentage points. By decomposing the US vertical shock measure, I find that the US tariff on a certain Chinese industry not only affected the industry's demand for foreign inputs from its own sector but also significantly reduced its demand for foreign inputs from other related sectors. Evidence also suggests that the China's retaliatory tariffs on the US imports and the China's most-favoured-nation (MFN) tariff cuts positively affected other countries' exports to China in non-intermediates - capital and consumption goods. However, the upstream effect due to the US tariffs on China prevails in aggregate with a larger magnitude as well as the greater share of intermediates in the exports to China. Finally, I examine the firm-level response to the industry-level US vertical shock using balance-sheets for Korean manufacturing firms. I put a particular focus on firms in Korea as it is the single largest exporting country to China. It is found that Korean firms in industries that are more exposed to the vertical shock of the US tariffs on China experienced a larger decline in their sales growth. The overall results are quite comparable to the cross-country analysis, confirming the significance of this vertical channel. The cross-border upstream propagation of local trade policy changes, as found in this paper, illustrates how tightly productions are interconnected across countries and sectors as well as the rising importance of China in this global supply chain.

This paper is, to the best of my knowledge, the first empirical attempt to assess the vertical linkage effects of the US-China trade war on third countries. There is growing literature on the economic impacts of the global trade tensions led by the US administration. Early work includes Amiti, Redding and Weinstein (2019), Amiti, Redding and Weinstein (2020), Fajgelbaum, Goldberg, Kennedy and Khandelwal (2019), Amiti, Kong and Weinstein (2020) and Huang, Lin, Liu and Tang (2019) that study the impact on firms and consumers in the US or China. My focus in this paper is to investigate the spillover impact of the trade war into other countries' trade that has been less explored thus far. In this respect, my study is broadly related to the literature on trade policy externalities which includes Bown and Crowley (2006)

[2]In 2016, the US was the single largest export market for China accounting for 18.4% of its total exports.

and Bown and Crowley (2007).[3] While these papers focus on horizontal competition between exporting countries as an underlying mechanism, my study looks at a different channel of trade policy spillover relating it to the literature on vertical specializations across countries and industries.

As another strand of research, there is growing interest in the role of production networks in the propagation of local economic shocks.[4] And some recent papers studying the trade war also underscore input-output linkages across countries. Handley, Kamal and Monarch (2020) leverage confidential US firm-trade transactions data to construct the product-level supply chain exposure to import tariffs. They document that the rising input costs due to US tariffs during 2018-19 dampened the US export growth for the affected products. Since detailed firm-level data on production networks are not readily available, some researchers employ industry-level IO tables in measuring the economy-wide production linkages.[5] Using industry-level data for US manufacturing sector and the US IO tables, Flaaen and Pierce (2019) find that the 2018 US import tariffs are associated with declines in employment and increases in producer prices through the rising costs of foreign inputs. Based on the information on US anti-dumping duties against China since the 1980s and the US IO tables, Bown, Coconi, Erbahar and Trimarchi (2021) document that the US import tariffs targeting Chinese upstream industries had a large negative impact on US downstream industries through rising input prices. While these papers highlight the input-output linkages in the US-China trade war through the lens of US firms or industries, I focus on its propagation to other 29 major trading partners with China.[6] Unlike the above-mentioned papers focusing on the input-cost (downstream) effect of the US import tariffs, my study sees the US tariffs as a negative demand shock against Chinese producers and attempts to capture the upstream effect of this shock on third countries.

The remainder of the paper proceeds as follows. Section 2 provides an overview of the US-China trade war and describes potential mechanisms relating the trade war to third

[3]Using the episode of US import restrictions in the 1990's, these papers show two channels through which a trade policy distorts the targeted country's trade with third countries - 'trade diversion' and 'trade depression' that are detailed in the later sections.

[4]For a review on recent empirical work on production networks, see Carvalho and Tahbaz-Salehi (2019).

[5]Early work using the IO tables to study production networks includes Bems, Johnson and Yi (2011) and Acemoglu, Akcigit and Kerr (2016). Bems, Johnson and Yi (2011) highlight the importance of vertical linkages in the trade collapse during the Great Recession of 2008-2009 based on a global IO framework. Using the detailed US IO tables, Acemoglu, Akcigit and Kerr (2016) empirically test the theory-based upstream and downstream network effects of demand and productivity shocks on the US economy.

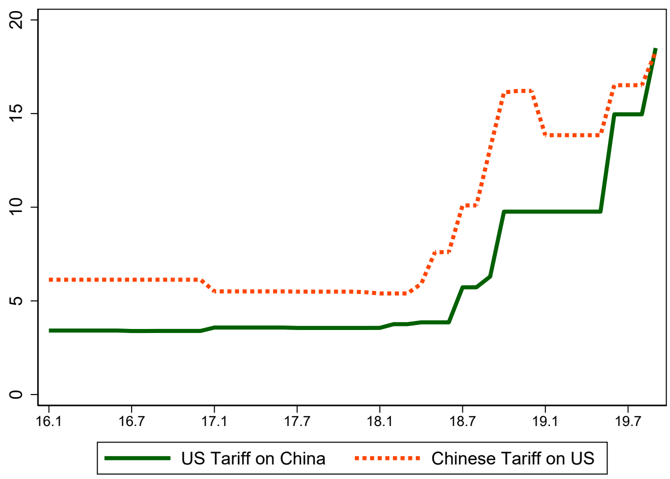
[6]Based on IMF Global Economic Outlook, the countries in my analysis account for 44% of the 2016 global GDP and the coverage of the global GDP rises to 75% once the US and China are excluded.

countries' exports. Section 3 and 4 list the data sources and detail the empirical strategy including the construction of a measure of the US vertical shock. Section 5 presents the results of cross-country analysis. Section 6 provides further evidence using balance-sheets of Korean manufacturing firms. Section 7 concludes.

2.2 The US-China trade war and China's imports

This paper focuses on a series of the large-scale tariff events between the US and China during 2018-2019. On April 2018, the US government announced its plan to impose tariffs on Chinese imports of $50 billion (under the part 1 and 2 of "China Section 301") following its investigation into China's unfair trade practices. And there were five rounds of the US tariff actions against China until September 2019 and, in each round, China retaliated by raising its own tariffs on US imports.[7] Figure 2.1 plots the evolution of bilateral tariffs between the US and China over time since 2016. We observe a dramatic rise in tariffs following a series of policy actions taken by both countries since 2018.

Fig. 2.1 US-China bilateral tariffs (%)



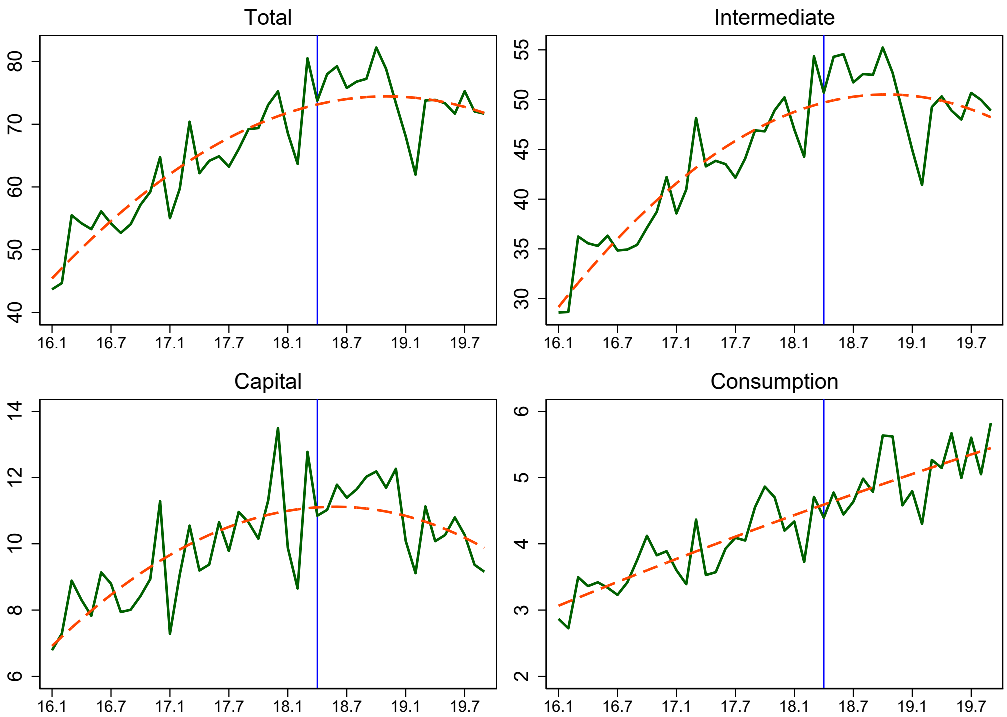
Note: Tariffs are weighted by 2015 import shares from the other party at HS 6-digit level.

Figure 2.2 displays monthly exports of other 29 countries towards China for each end-use classification by UN Broad Economic Categories (BEC) from January 2016. Note that the total export exhibits a parallel movement to the exports of intermediates as the latter accounts

[7]Even before April 2018, both countries raised their tariffs on one another for specific products such as solar panel, washing machine and aluminium. But the coverages and the trade volumes associated with these tariffs were relatively small.

for around two thirds of the total export to China.[8] Since the mid-2018 when the US-China trade war escalated, the exports to China experienced substantial declines in intermediates and capital goods following the tariff events. By contrast, the exports of consumption goods remained on an upward trend throughout the whole period.

Fig. 2.2 29 countries' exports to China by end-use category



Note: Monthly exports of 29 countries to China ($ billions) by end-use classification (UN Broad Economic Categories). Blue vertical line indicates April 2018 when the US government first announced plans to impose massive tariffs on China. Dashed lines are fitted polynomial trends.

What mechanism would drive these heterogeneous responses - particularly the dramatic fall in intermediates? Among others, one straightforward channel is the upstream propagation of US tariffs on China.[9] The US tariffs should reduce the US demand for Chinese imports which in turn dampens China's demand for foreign inputs from around the world. One can also imagine alternative channels related to horizontal competition. Specifically, there is a possibility that the US tariffs on China reduce third countries' exports to China in the same industry as the unsold Chinese products in US markets crowd out other foreign imports in

[8] The share of each category in total exports to China is 66.9% for intermediates, 15.8% for capital, 6.19% for consumption and 11.1% for others that are classified into multiple categories.

[9] Appendix 2.A provides a simple theoretical framework on the vertical linkage channels of the US-China tariff effects.

Chinese home markets. This is called 'trade depression' (Bown and Crowley (2006)). Both the vertical impact and trade depression due to US tariffs predict a negative impact on third countries' exports to China. But while trade depression could take place in any type of the end-use categories, the vertical propagation should occur primarily in intermediate inputs. Another horizontal channel is trade diversion; Chinese retaliatory tariffs against the US could result in substitutions of the US imports by other foreign products in Chinese home markets. This channel, as opposed to the previous two channels, predicts a positive impact on third countries. It is an empirical question as to which channel is dominant in other countries' responses to the trade war, and which will be examined in this paper.

2.3 Data

This paper makes use of four types of datasets from various sources: (1) 29 countries' monthly product-level exports from UN Comtrade, Eurostat and Taiwan customs, (2) the US and Chinese tariffs from Amiti, Redding and Weinstein (2019), Amiti, Redding and Weinstein (2020), Bown, Jung and Zhang (2019) and Worldbank WITS (World Integrated Trade Solution), (3) the 2012 Chinese IO table from China's National Bureau of Statistics and World IO tables from the 2012 World Input-Output Database (WIOD), and (4) quarterly balance-sheet data for 945 Korean manufacturing firms from the KISVALUE database.

Export data: For cross-country analysis, I use monthly exports of 29 countries towards China at the 6-digit Harmonized System (HS) product level. The countries here include 19 European countries, five Asia-pacific countries and three countries in America.[10] The choice of these countries is initially based on the availability of monthly export data at HS 6-digit level up to September 2019 in UN Comtrade database and the cross-country input-output matrices in WIOD. Among these countries, I choose the countries whose shares in China's total imports in 2016 are not smaller than 0.1 percent. I further include three countries - France, Netherlands and Taiwan - from alternative sources considering their large shares in China's total imports. Specifically, the exports of France, and Netherlands are sourced from Eurostat while I extract the exports for Taiwan from its customs office website. Altogether, these countries originated 50.5 (55.2) percent of the China's total (non-US) imports in 2016.

[10]See the appendix table 2.B1 for the full list of the countries with the size of their exports to China for 2016.

Tariff data: I obtain monthly US tariffs on Chinese imports at HS 10-digit level from Amiti, Redding and Weinstein (2020). For monthly Chinese tariffs on US imports, I use the HS 6-digit data from Amiti, Redding and Weinstein (2019) during 2016-2018 and extend them to September 2019 using Bown, Jung and Zhang (2019) that provide the HS 10-digit tariff changes in January and June in 2019 based on the statements by Chinese government. I further use the China's MFN tariff changes at the HS 10-digit level from May 2018 to June 2019 from Bown, Jung and Zhang (2019). I then link these MFN tariff changes with the data for 2016-2017 from the World Integrated Trade Solution (WITS). For merging into the above-mentioned export dataset, I average all these tariffs at the HS 6-digit level.

Input-Output tables: To identify vertical linkages between China and other countries, I exploit the detailed 2012 Chinese IO table. It comprises 139 industries at 5-digit Chinese Standard Industry Classification (CSIC) and, among these, I use 93 tradable industries that include agriculture, mining and manufacturing industries.[11] I obtain cross-country IO linkages from the 2012 World Input-Output Database (WIOD).[12] One drawback of the World IO is that it is constructed at the more aggregated 2-digit sector level of International Standard Industry Classification (ISIC) that consists of only 22 tradable sectors. To construct a measure of the vertical US shock at the more detailed CSIC industry level for each origin country, I adopt a proportionality assumption and disaggregate the elements of the World IO table using the industry-level Chinese IO. The detailed procedure is in the next section.

Firm data: For firm-level analysis, I use balance-sheets for firms in the Korean manufacturing sector from the proprietary KISVALUE database run by NICE - the Korea's largest credit information agency. Of the total of approximately 12,000 Korean manufacturing firms in the database, I initially obtain 1,247 firms that are listed in Korean stock markets as these firms report their financial statements on a quarterly basis. The items used in my analysis include total sales (domestic and foreign combined), total assets, capital intensity measured by fixed tangible assets per employee, credit score, firm age (years) and the firms' industry affiliations at 5-digit Korean Standard Industry Classification (KSIC).

[11] The remaining 46 industries in non-tradable sectors include energy production, construction and a wide range of private and public services industries that are not subject to tariffs. According to the 2012 imported input matrix for China in the WIOT, 82.0% of imported intermediates into China are used by tradable industries while the other 18.0% are used by non-tradable industries.

[12] The World IO table is constructed using both product-level trade flows across countries and national IO tables. For more details on WIOD, refer to Timmer et al. (2015).

2.3.1 Combining datasets

By combining these data, I construct two distinct datasets for my analysis. First, I build a trade dataset for cross-country analysis by aggregating the monthly exports for 29 countries and the US and Chinese tariffs at the CSIC industry level with the 2015 trade weights.[13] These data are aggregated at the quarterly frequency since monthly trade flows are noisy. I then plug the Chinese industry-level IO table into the aggregated trade dataset. Finally, I merge the sector-level World IO tables into the trade dataset.[14] The final sample covers the periods between 2017:Q1 and 2019:Q3 and includes 25,845 observations.

Second, I build a firm-level dataset by combining the balance-sheets for Korean manufacturing firms with the industry-level tariff variables. Of the initial 1,247 stock-listed manufacturing firms from the KISVALUE database, I trim the sample in the following steps; First, I drop zeros or negative values of assets and sales. I also drop firms with annual sales growth of more than 200% or less than -66% in any year between 2016 and 2018. Finally, I exclude firms whose records are missing at least once throughout 2016:Q1-2019:Q3.[15] The final sample contains 945 firms for the period between 2017:Q1 and 2019:Q3.

2.3.2 Aggregation by end-use classification

In our cross-country analysis, I run separate regressions by end-use classification of exports - intermediates in particular. While the end-use classification (UN BEC) is initially defined at HS 6-digit product level, the observation unit of my analysis is the CSIC industry. And most of the CSIC industries comprise more than one end-use category at the product level.[16] Considering this, I construct the sub-samples for each end-use category by (1) assigning the HS 6-digit exports and tariffs into bins for each end-use category, and then (2) aggregating the HS 6-digit units in each bin separately at the CSIC-industry level. Note that the US vertical shock measure is initially constructed using the CSIC-industry level IO tables and thus is identical across all the end-use categories.

[13] For matching between the CSIC 5-digit industries and the HS 6-digit products, I exploit the lookup table between the Korean SIC (KSIC) 5-digit industries and the HS 6-digit products provided by Statistics Korea as a bridge since the KSIC 5-digit industries and the CSIC 5-digit industries are very well aligned.

[14] The 2-digit ISIC sectors in World IO tables correspond to the first 2-digits of the CSIC-industries.

[15] Using the balanced panel of firms would alleviate any selection bias associated with entry or exit. Most of the trimming occurs in constructing the balanced panel.

[16] For instance, the CSIC-industry "Glass and glass products (30055)" includes intermediates (HS 6-digit of 700100, "Cullet and other waste and scrap of glass; glass in the mass"), consumption goods (701322, "Stemware drinking glasses, other than of glassceramics:Of lead crystal") and capital goods (701322, "Signalling glassware and optical elements of glass").

2.4 Empirical strategy

2.4.1 Measure of US Vertical Shock

The primary goal of this paper is to investigate upstream propagations of the US-China tariff shocks into third countries' exports to China. Since detailed information on production networks across countries is not available, I exploit the IO tables to build an industry-specific measure of vertical linkage exposure to US tariffs for each country exporting to China. Specifically, I define US Vertical Shock, denoted by $\mathrm{VS}_{i(c),t}^{US\to CN}$, as following:

$$\textbf{(Measure 1)} \quad \mathrm{VS}_{i(c),t}^{US\to CN} = \underbrace{\textstyle\sum_j \theta_{j,i(c)}^{F}}_{\text{Upstream propagation}} \underbrace{\left(\psi_j^{US}\Delta\tau_{j,t}^{US\to CN}\right)}_{\text{US tariff shock}}$$

where $\Delta\tau_{j,t}^{US\to CN}$ denotes the year-on-year changes in tariffs imposed by the US on Chinese imports of an CSIC industry j in tradable sectors at time t.[17] ψ_j^{US} is the US share in China's total export of industry j in 2015. $\theta_{j,i(c)}^{F} = \frac{\mathrm{Impint}_{j,i(c)}}{\sum_j \mathrm{Impint}_{j,i(c)}}$ is the origin country-industry specific import coefficient for China where $\mathrm{Impint}_{j,i(c)}$ denotes intermediate imports of input industry i into Chinese output industry j from origin country c in 2012. This import coefficient represents the input-output linkage between country c and China for each industry-pair.

It is quite intuitive how this measure captures the vertical propagation of US tariffs against China: First, the US tariff hikes dampen US demand for Chinese affected industry j ($\Delta\tau_{j,t}^{US}$). A dampened US demand would then reduce the production of Chinese industry j up to the importance of the US market for Chinese producers (ψ_j^{US}).[18] That in turn leads to a fall

[17]There are 93 CSIC industries in the tradable sectors - agriculture, mining and manufacturing. Among these, three industries do not export - “Support service to farming, forestry etc." (05005), “Mining support activity etc." (11011), “Slaughtering and processing of meat" (13016) and “Other electronic equipment (39090)".

[18]One might argue that it should be the China' total output of each industry rather than the China's total export that normalizes its exports to the US in computing ψ_j^{US}. There are two reasons for this choice. First is the well-documented fact in vast literature (Bernard, Jesen and Schott (2008), Amiti, Itskhoki and Konings (2014) etc.) that the production for exports tends to be more intensive in the use of imported intermediate than for domestic sales. Assuming that this pattern holds true for China's exports as well, it implies that the foreign input demand should be more sensitive to changes in demand from export markets than from the entire market including the Chinese domestic market. Second is the importance of processing exports which, despite the diminishing share, still account for 37.8% of the total China's export in 2014 (Kang and Liao (2016)). Processing trade has been adopted by Chinese exporters widely since the 1980's in an effort to boost their competitiveness in global markets. Chinese firms import all or part of raw materials and intermediate inputs, and re-export finished products after local processing or assembly (Yu (2014)). As the imports of inputs are directly linked to the final exports under this trading regime, it should further raise the sensitivity of China's imported input demand to their export market conditions. In this circumstance, if we use the US share in

in the Chinese industry j's demand for imported inputs of industry i from origin country c through the global IO structure ($\theta^F_{j,i(c)}$). Finally, for a foreign supplier i in country c, the total change in China's demand for its input is obtained from summing across all the Chinese output industries (j) that are targeted by the US tariffs.

One practical challenge in building this vertical shock measure is that there is no formal inter-country IO coefficients ($\theta^F_{i,j(c)}$) at the CSIC industry level as the WIOT is constructed at the more aggregated sector level. To tackle this problem, I introduce a proportionality assumption and disaggregate the sector-pair values of intermediate use in the WIOT into industry-pairs proportionally to the corresponding elements in the detailed Chinese IO table. The underlying assumption is that the use of imported inputs from each origin country is proportional to the use of total inputs for each industry-pair within each sector-pair. To illustrate, suppose transport equipment - which consists of the auto and shipbuilding industries - as a hypothetical output sector, and electrical machinery - which consists of the motor and battery industries - as an input sector. Also suppose that, according to the Chinese industry-level IO table, $5 (15) and $10 (20) of motors (batteries) are used as total inputs (domestic and foreign) by the auto and shipbuilding industries, respectively. Further assume that, according to the sector-level WIOT, $100 of imports of electrical machinery sector from Korea are supplied to the Chinese transport equipment sector. Then, I apportion $10 of these imports (=100*5/(5+15+10+20)) into the motor-auto industry pair and $40 (=100*20/(5+15+10+20)) into the battery-shipbuilding industry pair and so forth.[19] And these disaggregated import values for each industry-pair are used as the numerators of import coefficients $\theta^F_{j,i(c)}$ in which i is motor or battery industry, j is auto or shipbuilding industry and c is Korea in this example.

One might concern that the above-mentioned import proportionality is too strong to hold for imports from every origin country-industry pair. For instance, the total value of China's imports from Slovakia's electronics industry is quite small that it would be unrealistic to assume that the industry's inputs are used proportionally across all the Chinese output industries. Considering this, I also experiment with an alternative measure that simplifies the benchmark one; I use the *total* imports of industry i into Chinese industry j in constructing the import coefficients for China. This is based on the conjecture that the proportionality assumption is more plausible for total imports rather than origin country-specific.

China's total output assuming imported inputs are used equally by domestic and exporting producers, it would understate the magnitude of a foreign market shock on the China's overall foreign input demand. By the same logic, I admit that the choice of the US share in China's total export would possibly over-estimate the impact of the US tariffs on Chinese producers.

[19] Analogously, $30 (=100*15/(5+15+10+20)) and $20 (=100*10/(5+15+10+20)) of the imports are assigned to the motor-shipbuilding and battery-auto industry pairs, respectively.

$$\textbf{(Measure 2)} \quad \mathrm{VS}_{i,t}^{US\to CN} = \sum_j \theta_{j,i}^{F} \psi_j^{US} \Delta\tau_{j,t}^{US\to CN}$$

where $\theta_{j,i}^{F} = \frac{\mathrm{Impint}_{j,i}}{\sum_j \mathrm{Impint}_{j,i}}$ and $\mathrm{Impint}_{j,i}$ denotes the *total* intermediate imports of input industry i into Chinese output industry j from all the origin countries in 2012. Note that, unlike the benchmark measure, this alternative does not have a variation across origin countries.

2.4.2 Estimating equation

To examine the impact of the US-China trade war on other countries' exports, I estimate the following equation:

$$\Delta\mathrm{Export}_{i,c,t}^{CN} = \beta_1 \mathrm{VS}_{i(c),t}^{US\to CN} + \beta_2 \Delta\mathrm{Tariff}_{i,t}^{US\to CN} + \beta_3 \Delta\mathrm{Tariff}_{i,t}^{CN\to US} + \beta_4 \Delta\mathrm{Tariff}_{i,t}^{MFN} + \alpha_{i,c} + \eta_{c,t} + \nu_{s,t} + \varepsilon_{i,c,t}$$

where subscripts i, c, and t denote 89 tradable CSIC industries,[20] 29 countries and 11 quarters from 2017:Q1 to 2019:Q3. $\Delta\mathrm{Export}_{i,c,t}^{CN}$ denotes the mid-point growth rate of quarterly country-industry (i,c) exports to China relative to the previous year.[21] I use the year-on-year changes in quarterly exports to handle seasonality in high frequency trade flows. As a main variable of interest, $\mathrm{VS}_{i(c),t}^{US\to CN}$ aims to capture the negative upstream effect of the US tariffs on other countries ($\beta_1 < 0$). $\Delta\mathrm{Tariff}_{i,t}^{US\to CN}$ and $\Delta\mathrm{Tariff}_{i,t}^{CN\to US}$ are the year-on-year changes in the US and Chinese tariffs on one another that are multiplied by the US share in China's exports and imports in 2015, respectively. Specifically, $\Delta\mathrm{Tariff}_{i,t}^{US\to CN}$ is expected to have a negative coefficient ($\beta_2 < 0$) if the Chinese products intended for sale in the US market which remain in China due to the US tariffs end up crowding out other foreign imports in China's home markets. By contrast, $\Delta\mathrm{Tariff}_{i,t}^{CN\to US}$ should have a positive effect ($\beta_3 > 0$) if it results in substitutions for US imports by other foreign imports in China's home markets. Apart from these channels related to tariff changes between the US and China, I also control for the changes in China's MFN tariffs, denoted by $\Delta\mathrm{Tariff}_{i,t}^{MFN}$, that directly affect the third

[20] There are four out of 93 trabable CSIC industries that do not export - "Support service to farming, forestry etc." (05005), "Mining support activity etc." (11011), "Slaughtering and processing of meat" (13016) and "Other electronic equipment (39090)".

[21] That is, $\Delta\mathrm{Export}_{i,c,t}^{CN} = \frac{2*(\mathrm{Export}_{i,c,t}^{CN} - \mathrm{Export}_{i,c,t-4}^{CN})}{(\mathrm{Export}_{i,c,t}^{CN} + \mathrm{Export}_{i,c,t-4}^{CN})}$ where $\mathrm{Export}_{i,c,t}^{CN}$ indicates country c's exports of industry i to China at quarter t. This approach has an advantage over the logarithmic growth in accounting for adjustments in extensive margins (exit and entry) that are particularly rampant in high-frequency trade data.

countries' exports to China. A *reduction* in the China's MFN tariffs is predicted to have a positive effect on third countries' exports to China ($\beta_4 < 0$).

I add industry-country fixed effects ($\alpha_{i,c}$) to allow for the industry-country specific growth trend as well as country-time fixed effects ($\eta_{c,t}$) that control for macro shocks including exchange rate movements. To absorb other sector-specific business cycle and technological changes, I include sector-specific second-order polynomial trends or, more rigorously, sector-time fixed effects at the 2-digit sector level ($v_{s,t}$).[22]

One potential problem in the above equation is the unknown lag structure of the tariff effects. For instance, the tariffs could have a delayed effect on trade due to delivery lags in cross-border shipments or fixed contracts between sellers and buyers. There is also a possibility of anticipation effects; Importers and exporters may have reacted to the announcements of new tariffs and shifted their decisions even months before the policy changes come into place. These would then imply the regression identified from contemporaneous changes in tariffs may result in biased estimates. In the perspective of third countries, the lead or lagged effects of these sorts should be particularly pertinent to the bilateral tariff changes between the US and China rather than the China's MFN tariff changes that directly affect them. To account for these, I exploit the clear-cut before-after time dimension of the US-China tariffs as seen in figure 2.1 and treat a series of tariff changes since mid-2018 as a single event.

The estimating equation then becomes

$$
\begin{aligned}
\Delta\text{Export}^{CN}_{i,c,t} = {} & \beta_1 \widetilde{\text{VS}^{US\to CN}_{i(c)}} * \text{After}_t + \beta_2 \Delta\widetilde{\text{Tariff}^{US\to CN}_{i}} * \text{After}_t \\
& + \beta_3 \Delta\widetilde{\text{Tariff}^{CN\to US}_{i}} * \text{After}_t + \beta_4 \Delta\text{Tariff}^{MFN}_{i,t} + \alpha_{i,c} + \eta_{c,t} + v_{s,t} + \varepsilon_{i,c,t}
\end{aligned}
$$

where $\widetilde{X} \equiv \overline{X_{t\geq 2018:\text{Q2}}} - \overline{X_{t<2018:\text{Q2}}}$ with $\overline{X_{t\geq 2018:\text{Q2}}}$ denoting a mean of tariff shocks (X) on and after 2018:Q2. After_t is a time dummy equal to one if $t \geq$ 2018:Q2 and zero otherwise.[23]

[22]Since some ISIC 2-digit sectors include only one CSIC-industry, I group these sectors with other similar sectors together. Specifically, I combine “Crop and animal production, hunting and related service activities (A01)", “Forestry and logging (A02)" and “Fishing and aquaculture (A03") as a single sector group. I also group “Manufacture of paper and paper products (C17)" and “Printing and reproduction of recorded media (C18)" as “C17-18", “Manufacture of chemicals and chemical products (C21)" and “Manufacture of basic pharmaceutical products and pharmaceutical preparations (C22)" as “C21-22", “Manufacture of basic metals (C24)" and “Manufacture of fabricated metal products, except machinery and equipment (C25)" as “C24-C25", and “Manufacture of motor vehicles, trailers and semi-trailers (C29)" and “Manufacture of other transport equipment (C30)" as “C29-C30". The results using the initial definition of sectors are largely similar, however.

[23]The China's MFN tariff instead remains the initial form since, as noted above, other countries' response to the MFN tariff changes should be more immediate as directly affecting their exports to China.

Standard errors are clustered by the country-industry pairs.

2.5 Results

This section presents the results for the impacts of US-China tariff shocks on third countries' exports to China. Note that each shock is standardized to have zero mean and unit variance for all the coefficients to be directly comparable.

2.5.1 Baseline

Table 2.1 reports the baseline result for the growth rate of the 29 countries' exports of intermediates to China. Column 1 tests a parsimonious specification that only includes the US vertical shock. The coefficient is negative and highly significant at one percent. Columns 2 to 4 add other tariff shocks one after another. As shown in column 4, the coefficient for the US vertical shock remains significant even after including all other tariff shocks. While columns 1 to 4 control for sector-specific quadratic trends, column 5 tests the more rigorous sector-time fixed effects. The coefficient for the US vertical shock is essentially the same (-0.096 vs -0.091). Lastly, column 6 uses the alternative measure 2 of the US vertical shock and provides very similar estimates. These all together indicate that the industry-countries more exposed to upstream propagation of US tariffs on China saw a larger fall in their exports to China. The coefficients for other shocks are imprecisely estimated in all specifications.

One might question whether this US vertical shock measure indeed captures the propagation of US tariffs via input-output linkages or whether it erroneously picks up any other forces driving a similar decline in the overall exports to China. To address this concern, I run separate regressions for other end-use categories and compare the estimates. If the US vertical shock measure truly identifies the upstream propagation of US tariffs on China, it would not exert equally strong influence on the exports of non-intermediates.

Table 2.2 presents the result in which column 1 is for total exports (“Total") and column 2 is the baseline for intermediates (“INT"). Columns 3 to 4 are for capital (“CAP") and consumption goods (“CONS"), respectively. Columns 1 and 2 show that the US vertical shock significantly reduced third countries' total and intermediates exports. By contrast, I find no similar decline in the exports of non-intermediates, indicating that the US vertical effect is specific to trade in intermediates. The economic magnitude of this vertical impact is huge; A one standard deviation rise in the US vertical shock reduces the growth rates

Table 2.1 Impact of US-China trade war on 29 countries' intermediates exports to China

	Measure 1					Measure 2
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{VS}_{i(c)}^{US\to CN} * \text{After}_t$	-0.0965***	-0.0965***	-0.0957***	-0.0963***	-0.0914***	-0.1004***
	(0.0248)	(0.0248)	(0.0275)	(0.0275)	(0.0286)	(0.0316)
$\Delta\text{Tariff}_i^{US\to CN} * \text{After}_t$			-0.0015	-0.0007	0.0020	0.0073
			(0.0204)	(0.0204)	(0.0240)	(0.0245)
$\Delta\text{Tariff}_i^{CN\to US} * \text{After}_t$				-0.0245	-0.0309	-0.0325
				(0.0194)	(0.0199)	(0.0199)
$\Delta\text{Tariff}_{i,t}^{MFN}$		0.0057	0.0056	0.0054	0.0121	0.0125
		(0.0128)	(0.0129)	(0.0129)	(0.0140)	(0.0140)
# Observations	22,267	22,267	22,267	22,267	22,267	22,267
# Industry-countries	2,160	2,160	2,160	2,160	2,160	2,160
Adj-R2	0.0462	0.0462	0.0462	0.0463	0.0448	0.0448
Industry-country FE	✓	✓	✓	✓	✓	✓
Country-time FE	✓	✓	✓	✓	✓	✓
Sector quadratic trend	✓	✓	✓	✓		
Sector-time FE					✓	✓

Note: The dependent variable is mid-point growth rate of 29 countries' exports of intermediates to China at CSIC industry level. All the shocks are standardized to have zero mean and unit variance. Standard errors are clustered by industry-country pairs in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

of 27 countries' total and intermediates exports to China by 5.1 and 9.1 percentage points, respectively.

Turning to other shocks, the direct US tariffs on China (the 2nd row) did not affect third countries' exports in all product types, suggesting little evidence of 'trade depression'. Chinese retaliatory tariffs against the US (the 3rd row) increased the countries' exports of capital goods to Chinese markets as seen in column 3, which would reflect possible substitutions for US imports in the Chinese market ('trade diversion'). The China's MFN tariffs (the 4th row) did little to the exports of intermediates but they had a sizable impact on the exports of both capital and consumption goods. Columns 3 and 4 estimate that a one standard deviation *reduction* in Chinese MFN tariffs stimulates other countries' export growth to China by 3.6 and 3.0 percentage points for capital and consumption goods, respectively.[24] Despite that, the upstream effect of the US tariffs prevails in aggregate with the larger coefficient and the greater share of intermediates in the exports to China. In sum, the results reveal that the upstream propagation of the US tariffs played as a key channel through which the US-China trade war affected the rest of the world.

[24] These positive effects of the China's policy actions - the retaliatory tariffs on the US and the MFN tariff cuts - implies that the fall in capital goods exports to China could have been far more severe in the absence of these policies.

Table 2.2 Estimations by each end-use classification

	(1) Total	(2) INT	(3) CAP	(4) CONS
$VS_{i(c)}^{US\to CN} * After_t$	-0.0511**	-0.0914***	-0.0330	-0.0510
	(0.0253)	(0.0286)	(0.0481)	(0.0435)
$\Delta Tariff^{US\to CN} * After_t$	0.0154	0.0020	-0.0132	-0.0003
	(0.0199)	(0.0240)	(0.0167)	(0.0173)
$\Delta Tariff_i^{CN\to US} * After_t$	-0.0051	-0.0309	0.0170*	-0.0059
	(0.0129)	(0.0199)	(0.0094)	(0.0340)
$\Delta Tariff_{i,t}^{MFN}$	-0.0028	0.0121	-0.0356**	-0.0300*
	(0.0122)	(0.0140)	(0.0147)	(0.0153)
# Observations	25,845	22,267	8,723	13,525
# Industry-countries	2,449	2,160	840	1,372
Adj-R2	0.0478	0.0448	0.0094	0.0346
Industry-country FE	✓	✓	✓	✓
Country-time FE	✓	✓	✓	✓
Sector-time FE	✓	✓	✓	✓

Note: The dependent variable is mid-point growth rate of 29 countries' exports to China at CSIC industry level by each end-use category. The US vertical shock is based on the baseline measure 1. "INT" indicates a sub-sample for intermediates, "CAP" for capital goods and "CONS" for consumption goods. All the shocks are standardized to have zero mean and unit variance. Standard errors are clustered by industry-country pairs in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Appendix table 2.B3 presents the estimation results for each end-use category using the alternative measure 2 of the US vertical shock. The results are qualitatively the same.

2.5.2 Dynamic specification

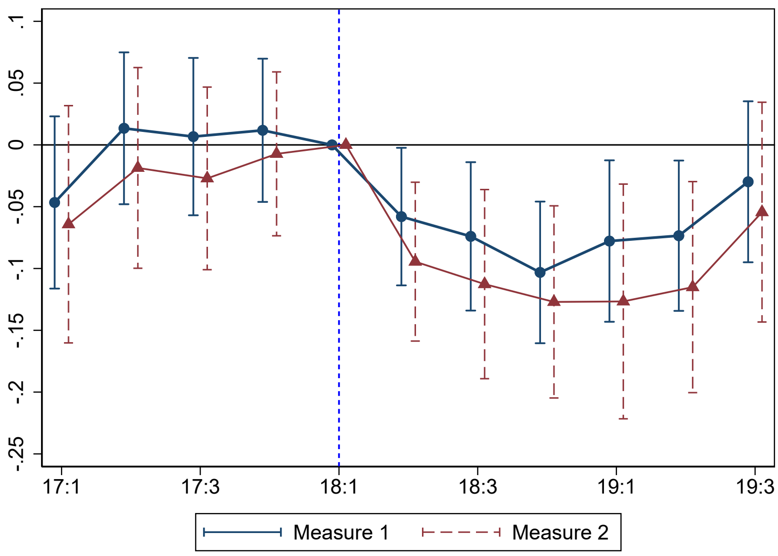
Next, I implement a more flexible regression using a full set of quarterly dummies interacted with each of the US-China trade shocks to examine how their impacts evolved over time:

$$\begin{aligned}\Delta \text{Export}_{i,c,t}^{CN} = & \textstyle\sum_t \beta_{1,t}(\widetilde{\text{VS}_{i(c)}^{US\to CN}} * D_t) + \sum_t \beta_{2,t}(\Delta \widetilde{\text{Tariff}_i^{US\to CN}} * D_t) \\ & + \textstyle\sum_t \beta_{3,t}(\Delta \widetilde{\text{Tariff}_i^{CN\to US}} * D_t) + \beta_4 \Delta \text{Tariff}_{i,t}^{MFN} \\ & + \alpha_i + \eta_{c,t} + \nu_{s,t} + \varepsilon_{i,c,t}, \quad \forall t \in \{2017{:}Q1, .., 2019{:}Q3\} \setminus 2018{:}Q1\end{aligned}$$

where D_t is an indicator for each quarter, with 2018:Q1 as the omitted category. This dynamic specification fully accounts for the potential anticipatory or delayed effects and also serves as a diagnostic test on pre-trends.

Figure 2.3 traces the point estimates and the 95% confidence intervals for measure 1 and 2 of the US vertical shock over time. The dashed vertical line indicates 2018:Q1 - one quarter before the start of the US-China trade war. The estimated coefficients for the US vertical shock not significantly different from zero up to 2017:Q4, telling that the significant US vertical effect on other countries' intermediate exports to China was not driven by pre-trends of any form. By contrast, the negative upstream effect turns significant beginning 2018:Q2 and becomes strongest during 2018:Q4-2019:Q1. Unsurprisingly, this is the period right after the third round of the US tariff hikes took place, which was the largest in scale during 2018.[25]

Fig. 2.3 Dynamic impact of US vertical shock



Note: Figure plots the point estimates of the US vertical shock for each quarter from the dynamic specification. The dependent variable is mid-point growth rate of 29 countries' exports of intermediates to China at the CSIC industry level. Error bars show 95% confidence interval.

[25]Full estimation results for the dynamic specification, by each end-use classification, are reported in appendix figure 2.B1 (using measure 1 of the US vertical shock) and 2.B2 (using measure 2). The exports of capital and consumption goods are little affected by the US vertical shock throughout the entire period. Other tariff shocks - the direct US and Chinese tariffs on one another - in column 2 and 3 in each figure do not appear to play any major role in most quarters in all product categories.

2.5.3 Decomposition: Own vs Other sectors

It is known that firms use a large fraction of inputs from their own industries and some papers focus on this within-industry input reliance in analysing the supply chain impact of economic shocks.[26] This section examines to what extent the upstream effect of the US tariffs on a foreign input industry is attributed to demand falls from the own versus other sectors in China. To see this, I decompose the US vertical shock as following:

$$\mathrm{VS}_{i(c)}^{\widetilde{US \to CN}} = \underbrace{\textstyle\sum_{k \in J_i} \theta^F_{k,i(c)} \psi^{US}_k \Delta\tau_k^{\widetilde{US \to CN}}}_{\text{Vertical shock from same sectors}} + \underbrace{\textstyle\sum_{k' \notin J_i} \theta^F_{k',i(c)} \psi^{US}_{k'} \Delta\tau_{k'}^{\widetilde{US \to CN}}}_{\text{Vertical shock from other sectors}}$$

where k and k' again denote the CSIC output industry in China and $i(c)$ indicates the CSIC input industry i in origin country c. J_i denotes the ISIC 2-digit sector to which the CSIC industry i belongs. The first component of the above decomposition corresponds to the upstream effect of falling demand from the own sector in China $(k \in J_i)$ while the second component captures that from other related sectors in China $(k \notin J_i)$.

The estimation result based on this decomposition is reported in table 2.3. Column 1 decomposes the baseline measure 1 while column 2 uses the measure 2. In either measure, the decline in other countries' exports of industry i towards China is found to be driven significantly by falling demand from other Chinese sectors hit by US tariffs ($k \notin J_i$), beyond that from the same Chinese sectors ($k \in J_i$). Specifically, the vertical impact stemming from the own sector is slightly larger (-0.0588 vs -0.0516) but the impact from all other related sectors combined are statistically even more significant. These suggest that the US tariffs on a certain Chinese industry reach far and wide into other foreign industries through the global IO linkages and, therefore, assessing the vertical propagation based solely on the within-industry input use would likely understate the true impact.[27]

[26] As evidenced by the diagonal elements of most I-O tables, the largest share of input purchases for an output industry usually comes from its own industry. As a study using information other than the IO tables, Handley, Kamal and Monarch (2020) exploit the firms' imports of the same HS 4-digit categories as their export products in evaluating the supply chain effect of the US import tariffs on the US exporters.

[27] This result also informs the evolving role of China in global value chain. Chinese manufacturers, armed with cheap labour costs, had grown rapidly by importing near-final products (from the same sector) and repackaging them for re-exports until the early 2000's (Yu (2014)). The strong upstream impact on foreign inputs from across other sectors imply that, unlike the previous decades, Chinese producers have engaged in more extensive parts of the multi-stage production using diverse foreign inputs from other industries rather the simple processing of foreign intermediates from the same sector.

Table 2.3 Decomposition: US vertical impact from own vs other sectors

	(1) Measure 1	(2) Measure 2
VS from Same sectors$_{i(c)}^{US\rightarrow CN} * \text{After}_t$	-0.0588*	-0.0612*
	(0.0333)	(0.0357)
VS from Other sectors$_{i(c)}^{US\rightarrow CN} * \text{After}_t$	-0.0516***	-0.0504**
	(0.0184)	(0.0199)
$\Delta\text{Tariff}_i^{US\rightarrow CN} * \text{After}_t$	0.0026	0.0044
	(0.0279)	(0.0284)
$\Delta\text{Tariff}_i^{CN\rightarrow US} * \text{After}_t$	-0.0284	-0.0302
	(0.0199)	(0.0199)
$\Delta\text{Tariff}_{i,t}^{MFN}$	0.0119	0.0125
	(0.0141)	(0.0141)
# Observations	22,267	22,267
# Industry-countries	2,160	2,160
Adj-R2	0.0446	0.0445
Industry-country FE	✓	✓
Country-time FE	✓	✓
Sector-time FE	✓	✓

Note: The dependent variable is mid-point growth rate of the 29 countries' exports of intermediates to China at the CSIC industry level. All the shocks are standardized to have zero mean and unit variance. Standard errors are clustered by industry-country pairs in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

2.5.4 Robustness

This section tests the robustness of the previous results on the US vertical effect.

(Sensitivity to specific regions or sectors)

To ensure that the previous result is not driven by specific countries or regions, I compare the estimates alternately dropping countries from one of the five geographic regions; Eastern Europe, Western Europe, Northern Europe, Asia-pacific and America.[28] As reported in appendix table 2.B4, the results from each sub-sample are largely similar to the baseline result. Another concern is a sensitivity to certain industries such as the electronics sector ('C26' in ISIC) that plays a crucial part in the formation of the Chinese supply chain. Related

[28]"Eastern Europe" includes Hungary, Slovakia, Poland, Turkey, Russia; "Western Europe" includes Germany, Netherlands, France, United Kingdom, Switzerland, Belgium, Ireland, Spain, Portugal and Italy; "Northern Europe" includes Denmark, Finland, Sweden and Norway; "Asia-pacific" includes South Korea, Japan, Taiwan, Australia and India; and "America" includes Mexico, Canada and Brazil.

to this, the US imposed a non-tariff sanction against Huawei, a Chinese electronics giant, on May 2019 which could also have affected trades between China and other countries. Columns 3 and 4 in appendix table 2.B5 run the regressions dropping the electronics sector and the quarter 2019:Q3, respectively. Without the IT sector, the coefficient for the US vertical effect becomes smaller (-0.096 $\rightarrow$ -0.076), implying the importance of this sector in China's supply chains. But the coefficient is still highly significant. Dropping 2019:Q3 does not change the result as well.

(Vertical impact due to Chinese tariffs)

This paper focuses on the vertical propagation of the US tariffs on China. It cannot be ruled out, however, that the Chinese retaliatory tariff on US imports also generates a separate vertical effect of any sort through the globally interconnected supply chains. This is more so considering that the US is among the largest exporters to China.[29] A simple theoretical framework in appendix 2.A predicts that the Chinese tariffs on US inputs could affect China's demand for third countries' inputs in two opposite ways. The first is a positive 'substitution effect' of the US inputs by other foreign inputs[30] and the second is a negative 'production cost effect' due to input complementarity. It is unknown which of these two different effects prevails over different time horizons. To check the importance of this alternative vertical channel, I construct a measure for the 'Chinese vertical shock' guided by the theory and test it along with other shocks. As reported in column 5 of appendix table 2.B5, the vertical effect due to Chinese tariffs is not significant. Note that the US vertical effect is not affected by the inclusion of this alternative vertical channel.

(2016 trade shares)

I use the 2015 trade shares of each country in aggregating the tariffs and building the measures of vertical shocks. This is based on the conjecture that 2015 is a more reliable pre-sample year not endogenous to the future trade war between the US and China. For comparison, I also test the 2016 trade shares as alternative weights. The results for regressions by end-use category are reported in appendix table 2.B6. The US vertical effect is essentially the same throughout, suggesting its robustness to the choice of the initial trade shares.

[29]In 2016, the US is the third largest exporter to China (8.5% in China's total import) following South Korea (10.0%) and Japan (9.2%).

[30]This is conceptually identical to trade diversion effect mentioned in the previous section except that the latter holds true for any type goods, not limited to intermediate inputs.

2.5.5 Discussion

Recall that, in the previous section, one standard deviation increase in the US vertical shock is estimated to reduce other countries' intermediates export growth to China by 9.1 percentage points. The magnitude of this estimated effect may seem large and one might question how a demand shock in one single export market could create such huge changes in Chinese producers' input demand, even considering the importance of the US market and the size of tariff changes.

One potential mechanism that could explain this large short-run elasticity would be inventory adjustments as pointed out by Alessandria, Kaboski and Midrigan (2010) and Bems, Johnson and Yi (2013). Specifically, the former paper shows that economies of scale in transportation and delivery lags for cross-border shipments give agents incentives to hold large inventories of imported goods. In response to a negative demand shock, imports may decline more than proportionally to the demand change because it also reduces the desired level of inventories, amplifying the overall effect on imports.[31] While Alessandria, Kaboski and Midrigan (2010) focus on inventories of final goods, the mechanism may apply to either US wholesalers of Chinese imports or Chinese producers importing intermediates or both.

The possibility that the economic impact of the US-China trade war may go beyond their trade exposures to one another is also raised by Handley, Kamal and Monarch (2020) in their study on US exporters. They find the estimated effects of the US import tariffs on US exports through rising foreign input costs is much large compared to what appears to be a fairly small cost shock in the aggregate. Likewise, for Chinese producers, the unprecedented tariff shocks from the largest export market (the US) and the huge uncertainty going forward would have put much more pressure on their operations than the size of tariffs. Some Chinese firms might have even been forced to drop out of exporting and importing altogether.[32] The vertical measure would probably capture part of these decisions beyond the immediate tariff-induced impact on their input demand.

[31] The magnitude of this mechanism could be huge. Alessandria, Kaboski and Midrigan (2010) suggest that inventory adjustments account for up to 20% of the drop in US imports during the trade collapse of 2008-2009. The impact could be largely heterogeneous across industries as well. In their case study on the US auto industry, imports fell by more than twice the sales of imported autos during the same period.

[32] One related hypothesis could be the presence of a global component of fixed export cost. For instance, Mau (2017) argues that firms should pay not only the conventional destination-specific fixed cost but a global (product-specific) fixed cost of exporting which results in economies of scale in serving multiple destinations. This implies that a negative demand shock in one foreign market, particularly a large one (the US), could induce Chinese firms to exit not only from the affected market but also from other destinations due to the increased per destination global fixed cost, which would result in much larger fall in their input demand.

Finally, it is important to note that the analysis in this paper is necessarily short-run in nature and the long-run effects of the trade war may differ. The longer-run effects of the tariffs should depend on whether firms see the trade war as transitory or permanent (Flaaen and Pierce (2019)). If permanent, for instance, less productive Chinese firms with a high reliance on the US market are more likely to exit from exporting while surviving firms would seek to diversify their export market portfolios away from the US to reduce the future risk. In either direction, these will all affect the long-run response of the China's trades with other countries.

2.6 Firm-level evidence from Korea

The analysis thus far presents cross-country evidence of the upstream effect of the US tariffs on China. In this section, I further implement a firm-level analysis to see how the industry-specific tariff shocks affected individual firms using balance-sheets for Korean manufacturing sector. Korea is an important testing ground in a sense that the country is the single largest exporter to China with its deep engagement in global value chain (Antràs and Chor (2018)).[33] Using the data for 945 Korean manufacturing firms, I run a regression for individual firms' sales growth on the industry-level tariff shocks:

$$\begin{aligned}\Delta\log(\text{Sales}_{f,i,t}) = {} & \beta_1 * \omega_i^{CN}\widetilde{\text{VS}_{i(KOR)}^{US\to CN}} * \text{After}_t + \beta_2 * \omega_i^{CN}\Delta\widetilde{\text{Tariff}_i^{US\to CN}} * \text{After}_t \\ & + \beta_3 * \omega_i^{CN}\Delta\widetilde{\text{Tariff}_i^{CN\to US}} * \text{After}_t + \beta_4 * \omega_i^{CN}\Delta\text{Tariff}_{i,t}^{MFN} \\ & + X_{f,t} + \alpha_f + v_{s,t} + \varepsilon_{f,i,t}\end{aligned}$$

where $\Delta\log(\text{Sales}_{f,i,t})$ is the four-quarter log difference in quarterly sales of Korean manufacturing firm f in industry i. Sales are deflated by the sector-level producer price. $X_{f,t}$ is a set of firm controls including the four quarter-lagged values of capital intensity, total assets, firm age and credit score. I also add firm (α_f) and sector-time fixed effects ($v_{s,t}$). It is likely that the tariff shocks associated with China have a bigger effect on firms in industries that

[33] Besides that, the merchandise exports account for over 40% of the Korea's gross domestic product (GDP) which is among the highest shares in advanced economies. This implies that a large fraction of Korean manufacturing firms engage in exporting - particularly to China as their largest foreign market - and should thus be exposed to the US-China trade war either directly or indirectly.

have a higher reliance on Chinese markets. Taking this into account, I multiply each tariff shock by the China's share in each Korean industry's 2015 exports (ω_i^{CN}).[34]

Table 2.4 Impact on Korean firms' sales growth

	(1)	(2)
$VS_{i(KOR)}^{US \to CN} * After_t$	-0.0359***	
	(0.0108)	
VS from Same sectors$_{i(KOR)}^{US \to CN} * After_t$		-0.0429
		(0.0352)
VS from Other sectors$_{i(KOR)}^{US \to CN} * After_t$		-0.0263**
		(0.0105)
$\Delta Tariff_i^{US \to CN} * After_t$	-0.0230	-0.0380
	(0.0179)	(0.0327)
$\Delta Tariff_i^{CN \to US} * After_t$	0.0214**	0.0208**
	(0.0107)	(0.0102)
ΔCN Tariff$_{i,t}^{MFN}$	-0.0015	-0.0002
	(0.0065)	(0.0065)
# Observations	10,361	10,361
# Firms	945	945
Adj-R2	0.138	0.138
Firm controls	✓	✓
Firm FE	✓	✓
Sector-Time FE	✓	✓

Note: The dependent variable is the four-quarter log difference in quarterly sales of Korean manufacturing firms. Each tariff shock is multiplied by China's shares in industries' 2015 exports (ω_i^{CN}). All the shocks are standardized to have zero mean and unit variance. Standard errors are clustered by industries in parentheses. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.4 presents the result. Column 1 presents that firms facing the US vertical shock suffered severe declines in their sales growth. A one standard deviation increase in the US vertical shock reduced the firms' sales growth by about 3.6 percentage points. There is also evidence that that Chinese retaliations positively affected Korean firms' sales, making up for part of the loss due to the US vertical shock. China's MFN tariff cuts, on the other hand, did not affect the firms' sales unlike in the cross-country analysis. Column 2 decomposes the US vertical shock in the same manner as in the previous section. It tells that a significant part of the US vertical effect on Korean firms were driven by falling demand from other sectors in China. The impact from the own sector in China, albeit a larger coefficient, is marginally insignificant.

[34] I also test without adjusting the tariff shocks by China's shares in industries' exports (ω_i^{CN}) and find a very similar result.

Finally, I test the dynamic specification using the interaction terms with full time dummies. As reported in appendix figure 2.B3, the US vertical shock turns out to have considerably dampened the growth of Korean firms until 2019:Q1 since the trade war began. Overall, these lend further support to the claim that the upstream propagation of the US tariffs is a key channel for the spillovers of the US-China trade war.

2.7 Concluding remarks

In this paper, I investigate global propagation of the US-China trade war to third countries. Constructing an origin country-industry specific measure of input-output linkages with China, I find new empirical evidence that the US tariffs on Chinese imports had a significant upstream effect on third countries. Industries with a higher vertical linkage exposure to the US tariffs experienced a substantial relative decline in their exports to China. Despite some mitigating effects of the China's retaliatory tariffs against the US and its MFN tariff cuts, the negative upstream effect of the US tariffs prevails in magnitude, leading to a substantial fall in aggregate export to China. The importance of this vertical channel is also confirmed in firm-level analysis on Korean manufacturing sector.

The cross-border upstream propagation of local trade policy changes as found in this paper illustrates how tightly productions are interconnected across countries and industries through the global supply chain. Further researches using more detailed data on ideally firm-to-firm international transactions, accounting for firm heterogeneity, will be welcome in exploring the trade policy spillovers through production networks.

Appendix 2.A Theoretical framework

In this appendix, I provide a simple theoretical framework to show how US-China tariff changes are associated with China's demand for third countries' intermediate inputs. Then, I relate it to the empirical measures of the vertical shocks used in the empirical analysis. The framework is in a partial equilibrium setting and focuses on the short-run impacts of the US-China tariffs.

2.A.1 Cost minimization

Consider a Chinese firm in tradable industries that uses labour and multiple imported intermediate inputs to produce a single differentiated product in the following Cobb-Douglas production function

$$Y_f = A_f L_f^{\alpha_f} \left(\prod_{j=1}^{N} \prod_{c=1}^{N_c} X_{f,j(c)}{}^{\gamma_{f,j(c)}} \right) \tag{2.A1}$$

where A_f denotes firm productivity which is exogenously given, L_f is labor and $X_{f,j(c)}$ indicate foreign imported input varieties j from origin country c that firm f uses, respectively. N and N_c denote the numbers of industries and origin countries, respectively. Constant returns to scale implies $\alpha_f + \sum_c^{N_c} \sum_j^N \gamma_{f,j(c)} = 1$. Total production cost is[35]

$$TC_f = wL_f + \textstyle\sum_j \sum_c \tau^v_{j(c)} v_{j(c)} X_{f,j(c)} \tag{2.A2}$$

where w is nominal wage and $v_{j(c)}$ is the unit producer price of foreign intermediate input $j(c)$ in the importer's currency and $\tau^v_{j(c)}$ is the ad valorem tariff imposed on input j from origin country c. Cost minimization yields marginal cost as

$$c_f = \frac{w^{\alpha_f}}{A_f \Omega_f} \left[\prod_{j=1}^{N} \prod_{c=1}^{N_c} \left(\tau^v_{j(c)} v_{j(c)} \right)^{\gamma_{f,j(c)}} \right] \tag{2.A3}$$

where $\Omega_f = \alpha_f^{\alpha_f} \prod_{j=1}^{N} \prod_{c=1}^{N_c} (\gamma_{f,j(c)}{}^{\gamma_{f,j(c)}})$ is a collection of technology parameters.

2.A.2 Profit maximization

The Chinese firm sells its product to home and foreign markets. I assume that each firm faces monopolistic competition in each market and consumers have a CES preference over

[35] For simplicity, I do not consider firm entry into exporting that would incur additional fixed costs.

differentiated products with elasticity of substitution between products common across destinations (σ). Then, the residual demand faced by a firm f in home and foreign market d are, respectively:

$$Q_f^H = \left(\frac{p_f}{P}\right)^{-\sigma} E \qquad Q_{f,d}^F = \left(\frac{\tau_{f,d}^o p_{f,d}}{P_d}\right)^{-\sigma} E_d \tag{2.A4}$$

where p_f and $p_{f,d}$ are the prices set by firm f for home and foreign market d. $\tau_{f,d}^o$ is the tariff imposed on the firm f's product by importing country d. E and E_d are demand shifters and P and P_d are the aggregate price indices for each market. Profit maximization in each market yields the common optimal price

$$p_f = p_{f,d} = \frac{\sigma}{\sigma - 1} c_f \,, \quad \forall d \tag{2.A5}$$

Market clearing for firm f's output is

$$Y_f = Q_f^H + \Sigma_d Q_{f,d}^F \tag{2.A6}$$

2.A.3 Foreign input demand

Let's turn to Chinese demand for non-US imported inputs. Combining the equations (2.A3)-(2.A6) together with the first-order condition for $X_{f,j(c)}$ in the cost minimization problem yields

$$\ln X_{f,j(c)} = \ln \gamma_{f,j(c)} - \ln v_{j(c)} + \ln c_f + \ln \left[Q_f^H + \Sigma_d Q_{f,d}^F \right] \tag{2.A7}$$

To focus on the short-run impact of tariffs, I assume that the terms related to firm technology ($A_f, \alpha_f, \gamma_{f,j(c)}$ and Ω_f) and macroeconomic factors (w, E, E_d, P, P_d, $\forall d$) are not affected by the changes in tariffs between the US and China. Further assume that the unit producer prices of foreign inputs ($v_{j(c)}$) also remain unchanged. Total differentiation of equation (2.A7) with respect to US tariffs on China $\tau_{f,US}^o$ and China's retaliatory tariffs on the US inputs $\tau_{j(US)}^v$ leads to

$$d \ln X_{f,j(c)} = \underbrace{-\sigma \psi_f^{US} d \ln \tau_{f,US}^o}_{\text{Vertical effect due to US tariff}} + \underbrace{(1-\sigma) \Sigma_j \gamma_{f,j(US)} d \ln \tau_{j(US)}^v}_{\text{Vertical effect due to China tariff}} \tag{2.A8}$$

where $\psi_f^{US} = \frac{Q_{f,US}^F}{Q_i^H + \sum_d Q_{f,d}^F}$ denotes the fraction of Chinese firm f' total output exported to US markets and $\gamma_{f,j(US)}$ is the cost share of input j sourcing from the US.

For non-US foreign input supplier $j(c)$ ($\forall c \neq US$), the total demand change from across all Chinese tradable industries, with $X_{j(c)} = \sum_f X_{f,j(c)}$, can be expressed as

$$\begin{aligned} d\ln X_{j(c)} &= \sum_f \theta_{f,j(c)}^F d\ln X_{f,j(c)} \\ &= \sum_f \theta_{f,j(c)}^F \left[-\sigma \psi_f^{US} d\ln \tau_{f,US}^o + (1-\sigma) \sum_j \gamma_{f,j(US)} d\ln \tau_{j(US)}^v \right] \end{aligned} \tag{2.A9}$$

where $\theta_{f,j(c)}^F = \frac{X_{f,j(c)}^F}{\sum_f X_{f,j(c)}^F}$. Equation (2.A9) informs that the vertical linkage effect associated with US tariffs ($d\ln \tau_{f,US}^o$) is definitely negative as a demand-side effect. The sign of the vertical effect related to Chinese tariffs ($d\ln \tau_{j(US)}^v$, $\forall j$) is determined by $(1-\sigma)$ which is negative as long as $\sigma > 1$. To interpret, there are two different channels through which Chinese tariffs on US inputs could affect its demand for other foreign inputs. First is a 'substitution effect'. The higher US input prices due to Chinese tariffs will result in substitution of the US imports into the other countries' inputs. This is conceptually identical to the trade diversion effect mentioned in the text except that the substitution effect in this section holds for intermediate inputs only. Second is that, with complementarity between different inputs, the higher US input prices due to Chinese tariffs increase the production cost of Chinese firms. The resulting demand fall and profit loss of Chinese producers would eventually lead to a fall in China's demand for every input, not only the US inputs. This negative 'production cost effect' is more pronounced if consumers are more price-elastic (higher σ).

2.A.4 Linking theory to data

To build an empirical counterpart of the vertical shocks from US-China tariffs that is consistent with equation (2.A9), I exploit the industry-level IO tables described in the text. The underlying assumption is that individual firms do not deviate systematically from the aggregate input-output structure of the industries that they belong to.

Two IO matrices are used: First is $\theta_{\mathbf{c}}^{\mathbf{F}}$ which is obtained by dividing China's intermediate imports from each origin country c for each input-output industry pair by China's total intermediate import of a given input industry from the origin country. $\gamma_{\mathbf{US}}$ is a matrix for the cost share of each US input in each Chinese industry's total output. Both $\theta_{\mathbf{c}}^{\mathbf{F}}$ and $\gamma_{\mathbf{US}}$

build on the origin country-specific import matrix that is constructed by disaggregating the sector-level World IO table proportionally to the industry-level Chinese detailed IO table.

$$\theta_{\mathbf{c}}^{\mathbf{F}} = \begin{bmatrix} \theta_{1,1(c)}^{F} & \theta_{1,2(c)}^{F} & \cdots & \theta_{1,N(c)}^{F} \\ \theta_{2,1(c)}^{F} & \theta_{2,2(c)}^{F} & \cdots & \theta_{2,N(c)}^{F} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{N,1(c)}^{F} & \theta_{N,2(c)}^{F} & \cdots & \theta_{N,N(c)}^{F} \end{bmatrix} \qquad \gamma_{\mathbf{US}} = \begin{bmatrix} \gamma_{1,1(US)} & \gamma_{1,2(US)} & \cdots & \gamma_{1,N(US)} \\ \gamma_{2,1(US)} & \gamma_{2,2(US)} & \cdots & \gamma_{2,N(US)} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{N,1(US)} & \gamma_{N,2(US)} & \cdots & \gamma_{N,N(US)} \end{bmatrix}$$

The vectors of industry-specific US and Chinese tariffs on one another's imports are denoted by

$$\psi^{\mathbf{US}}\boldsymbol{\Delta}\tau_{\mathbf{US}}^{\mathbf{o}} = \begin{bmatrix} \psi_1^{US}\Delta\ln\tau_{1,US}^{o} \\ \psi_2^{US}\Delta\ln\tau_{2,US}^{o} \\ \vdots \\ \psi_N^{US}\Delta\ln\tau_{N,US}^{o} \end{bmatrix} \qquad \boldsymbol{\Delta}\tau_{\mathbf{US}}^{\mathbf{v}} = \begin{bmatrix} \Delta\ln\tau_{1,US}^{v} \\ \Delta\ln\tau_{2,US}^{v} \\ \vdots \\ \Delta\ln\tau_{N,US}^{v} \end{bmatrix}$$

where ψ_i^{US} denotes the fraction of China's output of industry i exported to the US. Then, consistent with equation (2.A9), the $(\mathbf{Nx1})$ vectors of vertical shocks are derived as follows:

$$\text{US Vertical Shock} = \theta_{\mathbf{c}}^{\mathbf{F}}\psi^{\mathbf{US}}\boldsymbol{\Delta}\tau_{\mathbf{US}}^{\mathbf{o}} \tag{2.A10}$$

$$\text{Chinese Vertical Shock} = \theta_{\mathbf{c}}^{\mathbf{F}}\gamma_{\mathbf{US}}\boldsymbol{\Delta}\tau_{\mathbf{US}}^{\mathbf{v}} \tag{2.A11}$$

Note that the formula (2.A10) is a matrix expression of the benchmark measure 1 of the US vertical shock in the text except that I use the US share in the China's total export of industry i as ψ_i^{US} in practice, not the US share in China's total output of that industry, based on the reasoning in footnote 18. And the newly-constructed measure of the Chinese vertical shock (2.A11) is being tested in column 4 of appendix table 2.B5.

Appendix 2.B More statistics and results

Table 2.B1 China's imports by origin country

Origin country	Import value ($ billion)	Share (%)
South Korea	158.975	10.011
Japan	145.671	9.174
USA	135.120	8.509
Germany	86.109	5.423
Australia	70.895	4.465
Taiwan	66.400	4.182
Brazil	45.855	2.888
Switzerland	39.945	2.516
Russia	32.260	2.032
France	22.511	1.418
UK	18.681	1.176
Canada	18.337	1.155
Italy	16.713	1.053
India	11.764	0.741
Mexico	10.325	0.650
Netherlands	9.810	0.618
Belgium	6.874	0.433
Sweden	6.158	0.388
Spain	6.136	0.386
Ireland	5.297	0.334
Austria	5.027	0.317
Denmark	4.238	0.267
Hungary	3.464	0.218
Finland	3.455	0.218
Norway	3.231	0.203
Czechia	2.952	0.186
Turkey	2.785	0.175
Poland	2.538	0.160
Slovakia	2.410	0.152
Portugal	1.583	0.100

Note: This table is based on the China's imports from each country in 2016 from UN Comtrade except for Taiwan. The Import from Taiwan is the export value reported in the Taiwan Customs. The share is in terms of the China's total import in UN Comtrade.

Table 2.B2 Chinese Standard Industry Classification (CSIC)

CSIC-5	Industry Description	ISIC Rev. 4
01001	Farming	A01
02002	Forestry	A02
03003	Animal production	A01
04004	Fishery	A03
05005	Support service to farming, forestry etc.	A03
06006	Mining and washing of coal	B
07007	Extraction of crude petroleum and natural gas	B
08008	Mining of ferrous metal ores	B
09009	Mining of non-ferrous metal ores	B
10010	Mining and quarrying of non-metallic mineral	B
11011	Mining support activity etc.	B
13012	Manufacture of grain mill products	C10-C12
13013	Manufacture of prepared animal feeds	C10-C12
13014	Manufacture of crude and refined oil from vegetable	C10-C12
13015	Manufacture of sugar	C10-C12
13016	Slaughtering and processing of meat	C10-C12
13017	Processing of aquatic products	C10-C12
13018	Processing of other foods	C10-C12
14019	Manufacture of convenience food products	C10-C12
14020	Manufacture of milk and dairy products	C10-C12
14021	Manufacture of flavoring and ferment products	C10-C12
14022	Manufacture of other food products n.e.c	C10-C12
15023	Alcohol and alcoholic beverages	C10-C12
15024	Soft drink and refined tea products	C10-C12
16025	Tobacco products	C10-C12
17026	Spinning, weaving and fishing of cotton and chemical fibers	C13-C15
17027	Spinning, weaving and fishing of wool	C13-C15
17028	Spinning, weaving and fishing of bast and silk fibers	C13-C15
17029	Knitted and crocheted fabrics and articles, except apparel	C13-C15
17030	Made-up textile articles, except apparel	C13-C15
18031	Textile wearing apparel	C13-C15
19032	Leather, fur, feather and its products	C13-C15
19033	Footwear	C13-C15
20034	Processing of timbers and manufacture of wood products etc.	C16
21035	Furniture	C31_C32
22036	Paper and paper products	C17
23037	Printing and reproduction of recording media	C18
24038	Stationeries, musical instruments, products of arts, crafts, toys etc.	C31_C32
25039	Refined petroleum products, processing of nuclear fuel	C19
25040	Coke products	C19
26041	Basic chemicals	C20
26042	Fertilizers	C20
26043	Pesticides	C20
26044	Paints, printing inks, pigments and similar products	C20
26045	Synthetic materials	C20
26046	Special chemical products	C20
26047	Daily-use chemical products	C20

CSIC-5	Industry Description	ISIC Rev. 4
27048	Pharmaceutical products	C21
28049	Chemical fibers	C20
29050	Rubber products	C22
29051	Plastic products	C22
30052	Cement, lime and plaster	C23
30053	Products of plaster and cement and similar products	C23
30054	Brick, stone and other building materials	C23
30055	Glass and glass products	C23
30056	Ceramic and porcelain products	C23
30057	Refractory products	C23
30058	Products of graphite and other non-metallic minerals	C23
31059	Manufacture and casting of basic iron and steel	C24
31060	Processing of steel rolling processing	C24
31061	Ferroalloy	C24
32062	Manufacture and casting of non-ferrous metals and related alloys	C24
32063	Processing of non-ferrous metals rolling	C24
33064	Fabricated metal products, except machinery and equipment	C25
34065	Manufacture of boiler and prime mover	C28
34066	Metalworking machinery	C28
34067	Lifting and handling equipment	C28
34068	Pump, valve, compressor and similar machinery	C28
34069	Movie, office machinery and equipment, of projector and camera	C28
34070	Other general-purpose machinery	C28
35071	Machinery for mining, metallurgy, and construction	C28
35072	Machinery for chemical industry, timber, non-metal processing	C28
35073	Machinery for agriculture, forestry, animal production and fishery	C28
35074	Other special purpose machinery	C28
36075	Motor vehicles, except parts and accessories for motor vehicles	C29
36076	Parts and accessories for motor vehicles	C29
37077	Railway transport equipment	C30
37078	Boats and ships and floating devices	C30
37079	Other transport equipment	C30
38080	Generator and electric motors	C27
38081	Equipments for power transmission and distribution and control	C27
38082	Wire, cable, optical cable and electrical goods	C27
38083	Batteries	C27
38084	Household appliances	C27
38085	Other electrical machinery and equipment	C27
39086	Computer	C26
39087	Communication equipment	C26
39088	Broadcasting, television equipment, of radar and related equipment	C26
39089	Audiovisual apparatus	C26
39090	Electronic components and parts	C26
39091	Other electronic equipment	C26
40092	Measuring instruments and meters	C26
41093	Other manufacture	C31_C32

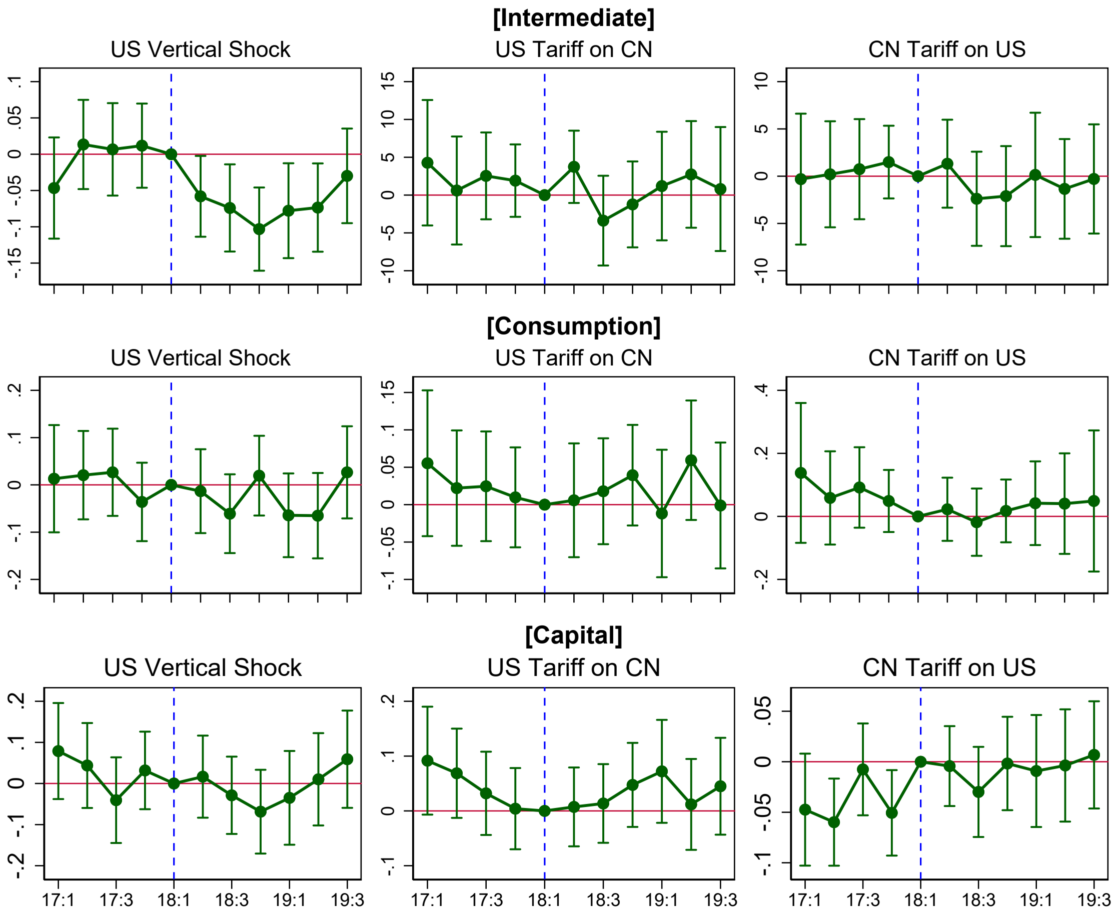
Note: Table lists 93 CSIC agriculture, mining and manufacturing industries and the corresponding 2-digit sectors in ISIC 4th revision.

Table 2.B3 Estimations by each end-use classification using Measure 2 of US vertical shock

	(1) Total	(2) INT	(3) CAP	(4) CONS
$\text{VS}_{i(c)}^{US\rightarrow CN} * \text{After}_t$	-0.0831***	-0.1004***	-0.0864	-0.0564
	(0.0288)	(0.0316)	(0.0580)	(0.0433)
$\Delta\text{Tariff}^{US\rightarrow CN} * \text{After}_t$	0.0304	0.0073	-0.0141	-0.0006
	(0.0213)	(0.0245)	(0.0166)	(0.0173)
$\Delta\text{Tariff}_i^{CN\rightarrow US} * \text{After}_t$	-0.0060	-0.0325	0.0168*	-0.0035
	(0.0129)	(0.0199)	(0.0094)	(0.0342)
$\Delta\text{Tariff}_{i,t}^{MFN}$	-0.0027	0.0125	-0.0363**	-0.0302**
	(0.0122)	(0.0140)	(0.0147)	(0.0153)
# Observations	25,845	22,267	8,723	13,525
# Industry-countries	2,449	2,160	840	1,372
Adj-R2	0.0483	0.0448	0.0098	0.0346
Industry-country FE	✓	✓	✓	✓
Country-time FE	✓	✓	✓	✓
Sector-time FE	✓	✓	✓	✓

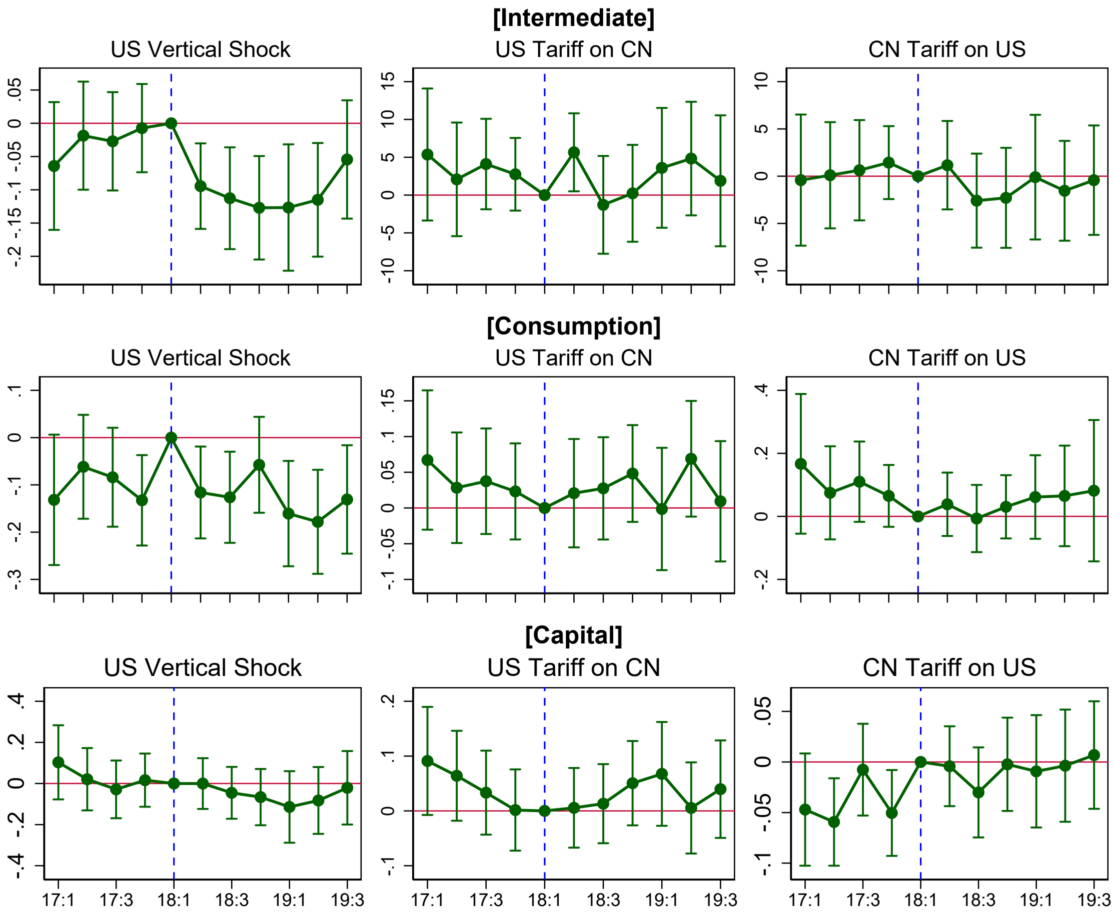
Note: This table uses the alternative measure 2 of the US vertical shock. The dependent variable is mid-point growth rate of 29 countries' exports to China at CSIC industry level. "INT" indicates a sub-sample for intermediates, "CAP" for capitals and "CONS" for consumption goods. All the shocks are standardized to have zero mean and unit variance. Standard errors are clustered by industry-country pairs in parentheses. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Fig. 2.B1 Full result for dynamic specification using Measure 1 of US vertical shock



Note: Figure plots dynamic regressions using the benchmark measure 1 of the US vertical shock. The 1st row is the results for intermediates, and the 2nd and 3rd rows are capital and consumption goods, respectively. Error bars show 95% confidence interval.

Fig. 2.B2 Full result for dynamic specification using Measure 2 of US vertical shock



Note: Figure plots dynamic regressions using the alternative measure 2 of the US vertical shock. The 1st row is the results for intermediates, and the 2nd and 3rd rows are capital and consumption goods, respectively. Error bars show 95% confidence interval.

Table 2.B4 Sensitivity by geographic region

	(1) Baseline	(2) No E-Europe	(3) No W-Europe	(4) No N-Europe	(5) No Asia	(6) No America
$VS_{i,c}^{US\rightarrow CN} * After_t$	-0.0914***	-0.0729**	-0.0955***	-0.0956***	-0.0996***	-0.0929***
	(0.0286)	(0.0353)	(0.0362)	(0.0292)	(0.0318)	(0.0295)
$\Delta Tariff_i^{US\rightarrow CN} * After_t$	0.0020	-0.0090	0.0032	0.0075	0.0103	-0.0013
	(0.0240)	(0.0263)	(0.0326)	(0.0249)	(0.0271)	(0.0247)
$\Delta Tariff_i^{CN\rightarrow US} * After_t$	-0.0309	-0.0274	-0.0362	-0.0362*	-0.0351	-0.0217
	(0.0199)	(0.0209)	(0.0299)	(0.0214)	(0.0233)	(0.0189)
$\Delta Tariff_{i,t}^{MFN}$	0.0121	-0.0016	0.0348*	0.0052	0.0123	0.0148
	(0.0140)	(0.0147)	(0.0185)	(0.0150)	(0.0166)	(0.0142)
# Observations	22,267	17,225	14,252	19,319	18,040	20,232
# Industry-countries	2,160	1,656	1,396	1,866	1,764	1,958
Adj-R2	0.0448	0.0403	0.0433	0.0457	0.0452	0.0472
Industry-country FE	✓	✓	✓	✓	✓	✓
Country-time FE	✓	✓	✓	✓	✓	✓
Sector-time FE	✓	✓	✓	✓	✓	✓

Note: The dependent variable is mid-point growth rate of the included countries' exports of intermediates to China at CSIC industry level. Each column estimates the regression dropping countries for the specified geographic region. "E-Europe" includes Hungary, Slovakia, Poland, Turkey and Czechia; "W-Europe" includes Austria, Germany, Netherlands, France, United Kingdom, Switzerland, Belgium, Ireland, Spain, Portugal and Italy; "N-Europe" includes Denmark, Finland, Sweden and Norway; "Asia" includes South Korea, Japan, Taiwan, Australia and India; and "America" includes Mexico, Canada and Brazil. All the shocks are standardized to have zero mean and unit variance. Standard errors are clustered by industry-country pairs in parentheses. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.B5 Further robustness check

	(1) Baseline	(2) NO IT sector	(3) No 2019:Q3	(4) CN Vertical Shock
$\text{VS}_{i,c}^{US\to CN} * \text{After}_t$	-0.0914***	-0.0750***	-0.0975***	-0.0910***
	(0.0286)	(0.0289)	(0.0302)	(0.0287)
$\Delta\text{Tariff}_i^{US\to CN} * \text{After}_t$	0.0020	0.0069	0.0059	0.0022
	(0.0240)	(0.0242)	(0.0246)	(0.0239)
$\Delta\text{Tariff}_i^{CN\to US} * \text{After}_t$	-0.0309	-0.0316	-0.0340	-0.0297
	(0.0199)	(0.0199)	(0.0211)	(0.0200)
$\text{VS}_{i,c}^{CN\to US} * \text{After}_t$				0.0125
				(0.0347)
$\Delta\text{Tariff}_{i,t}^{MFN}$	0.0121	0.0138	0.0164	0.0124
	(0.0140)	(0.0142)	(0.0144)	(0.0140)
# Observations	22,267	21,012	20,210	22,267
# Industry-countries	2,160	2,044	2,147	2,160
Adj-R2	0.0448	0.0450	0.0524	0.0447
Industry-country FE	✓	✓	✓	✓
Country-time FE	✓	✓	✓	✓
Sector-time FE	✓	✓	✓	✓

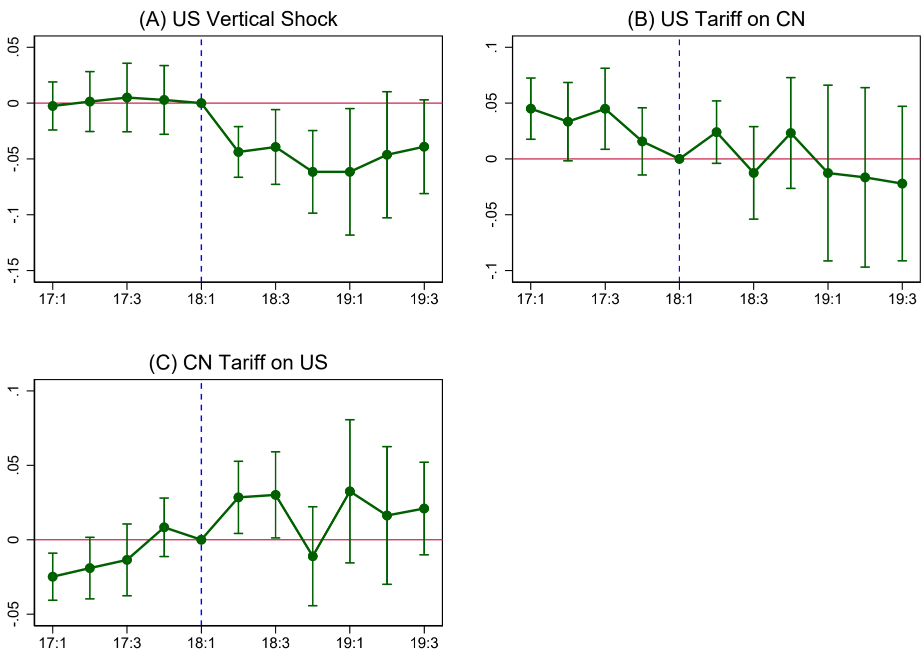
Note: The dependent variable is mid-point growth rate of 29 countries' exports of intermediates to China at CSIC industry level. Column 2 and 3 are estimates dropping IT sector ("C26" in ISIC 4 rev.) and 2019:Q3, respectively. Column 4 tests the measure of vertical shock related to Chinese tariffs ('Chinese vertical shock ') guided by equation (2.A11) in theory appendix. All the shocks are standardized to have zero mean and unit variance. Standard errors are clustered by industry-country pairs in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.B6 Estimations for all end-use categories: 2016 trade shares

	(1) Total	(2) INT	(3) CAP	(4) CONS
$\mathrm{VS}_{i(c)}^{US\rightarrow CN} * \mathrm{After}_t$	-0.0486*	-0.0854***	-0.0244	-0.0497
	(0.0252)	(0.0288)	(0.0480)	(0.0438)
$\Delta\mathrm{Tariff}^{US\rightarrow CN} * \mathrm{After}_t$	0.0022	-0.0127	-0.0252	-0.0021
	(0.0195)	(0.0249)	(0.0239)	(0.0169)
$\Delta\mathrm{Tariff}_i^{CN\rightarrow US} * \mathrm{After}_t$	0.0235	-0.0289	0.0278***	-0.0099
	(0.0144)	(0.0199)	(0.0099)	(0.0341)
$\Delta\mathrm{Tariff}_{i,t}^{MFN}$	-0.0022	0.0128	-0.0351**	-0.0269*
	(0.0122)	(0.0142)	(0.0146)	(0.0153)
# Observations	25,845	22,267	8,723	13,525
# Industry-countries	2,449	2,160	840	1,372
Adj-R2	0.0480	0.0448	0.0099	0.0345
Industry-country FE	✓	✓	✓	✓
Country-time FE	✓	✓	✓	✓
Sector-time FE	✓	✓	✓	✓

Note: Estimations by each end-use category using the 2016 trade shares in constructing the trade shocks. All the shocks are standardized to have zero mean and unit variance. Standard errors are clustered by industry-country pairs in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Fig. 2.B3 Dynamic impact of tariff shocks on Korean firms' sales growth



Note: Figure plots regressions with full time dummies interacted with each tariff shock on Korean firms' sales growth. Error bars show 95% confidence interval.

Chapter 3

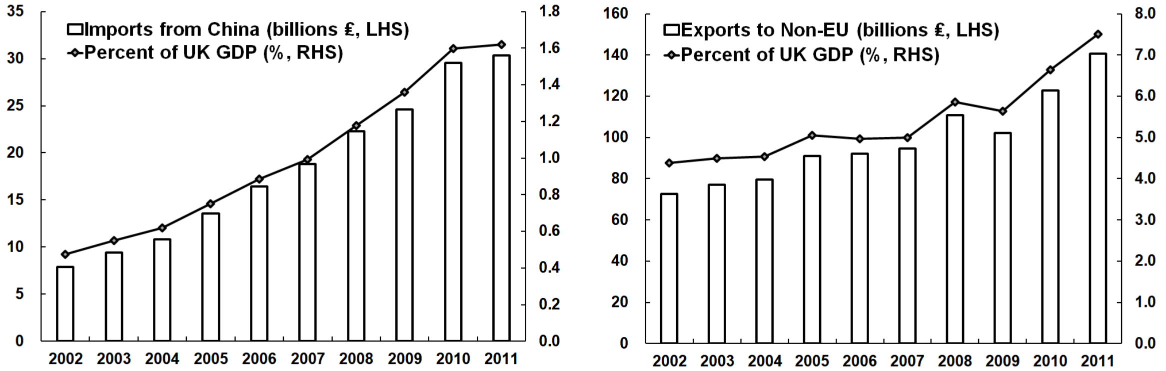
The impact of trade on R&D: Evidence from UK firms

3.1 Introduction

How trade affects innovation is a central question for academics and policy makers as it determines the fundamental gains from a trade liberalization. The recent literature emphasizes the importance of dynamic gains from trade: Trade may induce an endogenous change in firm innovation and productivity. A large body of literature exploring this question highlights three main channels: (1) export market access (Lileeva and Trefler (2010) and Bustos (2011)), (2) import competition (Bloom, Draca and Van Reenen (2015) and Autor et al. (2020)) and (3) access to imported inputs (Amiti and Konings (2007) and Goldberg, Khandelwal, Pavcnik and Topalova (2010)). Several of these papers find that improved access to export markets and imported inputs following trade liberalizations raises firm productivity, primarily in developing countries. For import competition, however, empirical evidence is mixed: Autor et al. (2020) find a negative impact of Chinese competition on innovation for US firms while Bloom, Draca and Van Reenen (2015) document increased patenting and technological upgrading by European firms facing Chinese import competition. Theories on how product-market competition affects innovation also suggest conflicting predictions (Shu and Steinwender (2019)). On the one hand, competition reduces the potential rents that firms can enjoy from innovating in a given market and thus their incentive to invest in innovation (the so called "Schumpeterian effect"). On the other hand, tougher competition may stimulate firms to develop entirely new types of products or to introduce more efficient processes to shield themselves from the competition (the "escape-competition effect").

Using UK administrative data, this paper empirically investigates how trade affects R&D investment of UK manufacturers over 2002-2011. The data used in this analysis are drawn from three datasets – (1) firm R&D expenditures from UK corporate tax return data, (2) UK firms' trade transactions with extra-EU countries, and (3) the Business Structure Database (BSD) which contains key firm characteristics for a near population of UK enterprises. To explore the long-debated impact of import competition, I follow the leading literature that focuses on the Chinese expansion in global trade following China's accession to the World Trade Organization (WTO) in 2001. Relative to the existing literature such as Bloom, Draca and Van Reenen (2015) and Autor et al. (2020) which focuses on import competition, I evaluate two channels - import competition and export demand - jointly using firm-level trade data. The last decades witnessed a rapid trade integration around the globe, in which firms in one country not only confronted increasing foreign competition but also gained better access to export markets. For the UK, its merchandise imports from China as a ratio of the UK's gross domestic product (GDP) soared from 0.48 percent to 1.62 percent between 2002 and 2011 (left-hand side of figure 3.1). During the same period, the UK's merchandise exports to non-EU destinations as a share of the UK's GDP almost doubled from 4.38 percent to 7.51 percent (right-hand side of figure 3.1).[1] In these circumstances, a joint investigation into both channels will help us gain a better insight into the overall impact of globalization and allow us to assess their relative importance.

Fig. 3.1 UK merchandise trades



Note: 'Non-EU' indicates all destinations excluding 27 EU membership countries. Source: Office for National Statistics (ONS).

[1] The non-EU countries indicate all other countries except for 27 EU membership countries as of 2021. In fact, there were two major changes in the number of EU membership countries between 2002 and 2011. In 2004, 10 countries joined EU as new members; Cyprus, Malta, Czech Republic, Slovak Republic, Estonia, Latvia, Lithuania, Hungary, Poland and Slovenia. In 2007, Bulgaria and Romania gained the EU membership as well.

An important feature of this paper is in its focus on firms' R&D expenditure – a key innovation input - as an outcome of interest. Most previous work uses patenting or total factor productivity (TFP) to measure firm innovation. However, changes in TFP could reflect other forces like markup changes rather than productivity changes due to innovation (Shu and Steinwender (2019)). Patenting, a recently popularized measure of innovation output, is not without limitations: Not all innovations are patented, nor does patenting necessarily represent new innovation as firms may patent to protect their existing knowledge from threats of imitation by competitors (Aghion et al. (2018)). The information on firms' R&D expenditure in this paper is based on UK corporate tax returns from the UK tax authority - Her Majesty's Revenue and Customs (HMRC). And, relative to previous studies, there are two advantages in using the R&D expenditure from administrative data: a more precise definition of R&D and a broader coverage of firms. First, the UK tax return dataset allows us to infer the actual amount of R&D expenditures of individual firms. In 2000, the UK government introduced an R&D tax incentive to financially support innovation activities of small and medium firms (SMEs), which was extended to large firms in 2002.[2] The reported R&D is validated and corrected by HMRC to the extent that the expenditure complies with the HMRC's definition of innovation activity.[3] The majority of prior work using firm R&D relies on survey data or financial statements of listed firms which may omit some data as R&D is not a compulsory item to report.[4] Second, this paper covers a large number of SMEs. Analysing these SMEs together with larger firms not only sheds light on the behaviours of firms across the firm-size distribution, but also has more relevance for policies to promote the growth of these firms.

To summarize key results, I find strong evidence of an adverse impact of import competition on firms' innovation efforts. UK firms in industries that are more exposed to rising

[2]The UK R&D tax credit allows firms to deduct their qualified R&D spending with an enhanced rate from their taxable profits. Firms initially claim a tax credit for a given amount of enhanced R&D expenditure based on the enhancement rate set by HMRC. The tax authority derives the value of the actual R&D spending of the firm from this enhanced expenditure. For details on the UK's R&D tax relief scheme, see Dechezleprêtre et al. (2016) and Guceri and Liu (2019).

[3]HMRC Corporate Intangibles and R&D Manual sets three main categories of qualifying R&D expenditures for tax relief claims - staffing costs, consumables (water, electricity etc.) and software that are directly used for R&D. The R&D expenditure in the HMRC dataset is different from the UK business R&D statistics in the Business Enterprise Research and Development (BERD) data published by the ONS. It is estimated that the R&D expenditure which qualified for tax relief reported to HMRC amounts to approximately 70% of the R&D in BERD for 2011. The difference may be because HMRC adopts a narrower definition of R&D for tax purposes. For instance, BERD admits R&D spending on capital investment while HMRC R&D only covers current expenses (Dechezleprêtre et al. (2016)).

[4]For instance, among the papers using R&D data in part of their analysis, Bloom, Draca and Van Reenen (2015) use European listed firms from Amadeus. Xu and Gong (2017), Hombert and Matray (2018) and Autor et al. (2020) study US firms from Compustat. Iacovone (2012) uses survey data on Mexican manufacturers that are more representative of large firms. Bøler, Moxnes and Ulltveit-Moe (2015) also use survey data for a subset of Norwegian firms with 50 or more employees.

Chinese imports experienced a larger fall in their R&D investment. To account for the increased availability of Chinese inputs, I also examine firms' own imports from China. I find no evidence of the impact of firms' use of Chinese imports on their R&D. The negative R&D response to import competition is in line with the Schumpeterian hypothesis, which is also supported by Autor et al. (2020). As another trade channel, I verify a significant and positive effect of export demand on firm R&D. The economic magnitudes of both channels are substantial. A one standard deviation rise in Chinese import penetration is associated with a decline in firms' R&D spending of 26 percent. Interestingly, a positive export demand shock could more than compensate for the adverse impact of tougher competition: A one standard deviation rise in a firm-level measure of export demand boosts firms' R&D spending by about 55 percent. These large magnitudes suggest that changes in the trade environment surrounding firms are a key driver for their investment in innovation.

I further examine heterogeneous effects of foreign competition and export demand shocks depending on firms' initial conditions. For Chinese competition, there is no significant difference in R&D responses across the firms' productivity distribution. Instead, I find some evidence that firms that initially engaged in exporting were less hurt by rising import competition. It is possibly because these firms that had already entered into exporting could more easily reallocate their sales abroad away from the shrinking domestic market. In contrast to my findings on the competition channel, I observe strong heterogeneity in the effects of export demand across firms' productivity: Firms whose productivity is higher in the initial periods raise their R&D by much more in response to a foreign demand shock. These findings together imply that the innovation efforts by purely domestic and less profitable firms were most adversely affected by globalization, leading to a widening productivity gap across firms.

This research relates to a broad empirical literature on trade and innovation. First, this paper revisits the long-standing debate on the relationship between import competition and innovation. While empirical evidence on this relationship is inconclusive (in line with the theoretical ambiguity), Shu and Steinwender (2019) point out that studies on developing countries such as Pavcnik (2002), Fernandes (2007), Amiti and Konings (2007), Topalova and Khandelwal (2011) and Iacovone (2012) provide supportive evidence of the positive impact of foreign competition on productivity and innovation. More recent work on advanced economies presents more conflicting evidence in the context of a drastic rise in Chinese imports as seen in Bloom, Draca and Van Reenen (2015) and Autor et al. (2020). This paper adds another case-study for an advanced economy, the UK, but concentrates on the response of firm R&D rather than a measure of innovation outputs such as patenting. This paper also adds to literature on the interaction between export market access and technology upgrading of individual firms including Lileeva and Trefler (2010), Bustos (2011), Coelli, Moxnes and Ulltveit-Moe (forthcoming) and Aghion, Bergeaud, Lequien and Melitz (2018). Several studies argue that an increased export market size raises the profitability of firms' investment in technology and thus encourages firm innovation. By constructing a firm-level measure of the export demand shock, I examine the role of exporting opportunities in determining firm R&D and assess its quantitative importance in comparison to import competition.[5]

The remainder of the paper proceeds as follows. Section 2 describes the data source and section 3 details the empirical strategy. Section 4 presents the empirical results. Section 5 concludes.

3.2 Data

The empirical analysis builds on three datasets: (1) UK firms' R&D expenditure derived from the HMRC corporate tax returns; (2) the HMRC overseas trade dataset; (3) the UK's Business Structure Database (BSD) from the Office of National Statistics (ONS) that contains firm characteristics such as employment and industry affiliation of a near population of UK enterprises.[6]

R&D expenditure data: The key variable in my analysis is the amount of R&D expenditure of each firm in each year that is reported for R&D tax relief claims to Her Majesty's Revenue and Customs (HMRC) - the UK tax authority. This information is from the Research and Development Tax Credits (RDTC) dataset which is an extension of the UK corporate tax return dataset (CT600).[7] The amount of R&D expenditure is initially reported by the firm and is further validated and corrected by the tax authority using other information on the

[5]For some recent works studying the two channels together, Berthou, Chung, Manova and Sandoz (2020) use sector-level data for 14 European countries to investigate the impact of exogenous shocks to export demand and import competition on aggregate productivity. Lim, Trefler and Yu (2018) conduct a comprehensive study on the impact of export market size and foreign competition using Chinese firm data.

[6]The HMRC administrative datasets can be accessed only within a designated HMRC facility - HMRC Datalab. The HMRC Datalab is an Research Data Centre (RDC) that allows approved researchers to use HMRC data in a secure environment. Merging these data with other datasets like the BSD in this paper is also subject to permission from HMRC.

[7]The CT600 dataset is a confidential panel dataset constructed by the UK tax authority (HMRC) which contains corporate tax returns or assessments made from the returns for the universe of companies in the UK. See Dechezleprêtre et al. (2016) for more details on the CT600 dataset.

firm's tax returns.[8]

Business Structure Database: For key firm characteristics, I use the UK's Business Structure Database (BSD) which is a snapshot of the Inter Departmental Business Register (IDBR) – a live register of UK enterprises maintained by the Office for National Statistics (ONS). The BSD contains details on the near universe of active UK firms covering nearly 99% of UK economic activity. The BSD used in this paper contains information such as enterprise reference number (Entref), employment, turnover, country of ownership, industry affiliation based on the UK Standard Industrial Classification (UK SIC) 2003 revision, year of birth (company start-up date) as well as location of company by UK postcode over the period between 1998 and 2012.

Firm-level trade data: Another data source for my analysis is the firm-level overseas trade dataset from HMRC. The trade dataset contains information on UK firms' import and export declarations with extra-EU countries. These include monthly information on the value of exports and imports at the 8-digit Combined Nomenclature (CN) product-level and countries of destination or origin. The dataset covers the period from 1996 to 2011.[9]

In addition to these datasets, I use the UN Comtrade database for bilateral trade flows at the HS 6-digit level to construct some trade variables detailed later.

I combine the three datasets using the look-up tables provided internally by HMRC that match the different firm identifiers in each dataset. The constructed dataset, labelled as 'BSD-R&D-Trade', is an unbalanced panel of 4,107 firms between 2002 and 2011; the total number of firm-year observation is 28,966.[10] These firms are R&D performing firms in manufacturing sectors that reported a positive R&D spending to HMRC at least once between 2002 and 2011. Appendix table 3.B1 presents some descriptive statistics. In this dataset, the mean turnover and employment are £7.6 million and 52.1 persons with standard deviations of 68.3 and 239.9, respectively. These firms are smaller in size compared to major European firms that were studied in Bloom, Draca and Van Reenen (2015) with a mean employment of

[8]Note that the qualifying R&D expenditures are available only for the R&D-tax-relief-claiming firms for the years in which they make the claims. Therefore, as in Dechezleprêtre et al. (2016) and Guceri and Liu (2019), I assume that non-claiming firms did not spend on R&D.

[9]My analysis covers UK firms' trade with non-EU countries only because data on within-EU transactions are available from 2005, while the non-EU transactions are available from 1996.

[10]For the detailed process of combining the datasets, see appendix 3.A.

739.5.[11] In order to assess the robustness of the results, I also use an alternative dataset that combines the BSD and the R&D data but is not merged with firm-level trade data (labelled as ‘BSD-R&D’). This alternative sample includes more firms - 4,798 in total - and, using this dataset, I test the robustness of my findings on an industry-level import competition measure which does not require firm-level trade information. By the number of firms, this sample is estimated to cover more than 70% of UK manufacturing firms that report R&D tax credit claims for 2011.[12] In terms of R&D amount, firms in this sample are representative of SMEs in UK manufacturing, accounting for approximately 62 percent of the total qualifying R&D expenditures under the SME tax credit scheme. It further covers around 14 percent of the total R&D expenditures reported under the large company tax credit scheme.[13]

3.3 Empirical strategy

In this section, I set up an estimating equation for UK firms’ R&D that includes the measures of Chinese import competition and firm-specific export demand as key determinants. I then detail how these measures are constructed. The baseline estimating equation is

$$\begin{aligned}\mathrm{RnD}_{f(k),t} &= \beta_1 \mathrm{IMP}^{CN}_{k,t-1} + \beta_2 \mathrm{EXD}^{nEU}_{f,t-1} + \gamma \log(\mathrm{Import}_{f,t-1}) \\ &+ \mathrm{Controls}_{f,t-1} + \alpha_f + \delta_{s,t} + \nu_{r,t} + \varepsilon_{f,t}\end{aligned}$$

where subscripts f, k, s, r and t denote firm, UK SIC 4-digit industry, UK SIC 2-digit sector, geographic region defined by the first one or two letters of the outward code in the UK postcode and year, respectively. The outcome variable $\mathrm{RnD}_{f(k),t}$ is either the logarithm of firm R&D expenditure or an R&D dummy. In the case of the log R&D, I add one to the original R&D amounts before the log transformation due to many zeros reported for R&D

[11] An interesting aspect of the firms in our dataset is that, albeit small in size, more than half of them engaged in extra-EU trade. This is somewhat inconsistent with the Melitz model that only large (and more productive) firms import and/or export. Exporting by many small firms is also found in Lileeva and Trefler (2010) that use Canadian plant-level data.

[12] This is based on Fowkes, Sousa and Duncan (2015) - a technical report published by HMRC which provides the number of R&D tax credit claims by each 2-digit UK SIC industry in 2012.

[13] Until 2012, HMRC operated two distinct R&D tax credit schemes based on the firm size - “Large Company” and “SME”. And our R&D dataset over the sample period (2002-2011) contains information on the specific scheme to which a firm’s R&D tax claim is classified. After 2012, the UK government introduced another R&D support scheme - Research and Development Expenditure Credit (RDEC) - in April 2013 and gradually replaced the Large Company tax credit scheme which was abolished in the financial year 2016-17.

expenditures.[14] I use an R&D dummy as an alternative outcome because I hypothesize that, at least for some firms, R&D is a binary decision.

The above equation relates firm R&D expenditure to trade exposures, as the main focus of this paper, together with other firm characteristics. The first term $\mathrm{IMP}^{CN}_{k,t-1}$ aims to test the two conflicting hypotheses as to whether foreign competition hinders ("Schumpeterian effect") or spurs ("escape competition effect") firm innovation. As in the previous literature, I focus on the rise of Chinese imports for its salience and enormous scale over the last two decades. As the second determinant, $\mathrm{EXD}^{nEU}_{f,t-1}$ evaluates the importance of export market size in firms' R&D decisions. Intuitively, the larger the product market is, the more profitable it would be for firms to invest in new inventions.[15]

(Chinese competition) Following the prior literature, I measure the exposure of UK firms to Chinese competition using UK imports from China at the SIC 4-digit industry level normalized by the UK industry's output:

$$\mathrm{IMP}^{CN}_{k,t} = \frac{\mathrm{Import}^{CN}_{k,t}}{\mathrm{Turnover}_{k,2000}}$$

where $\mathrm{Import}^{CN}_{k,t}$ denotes Chinese imports into the UK in industry k in year t and $\mathrm{Output}_{k,2000}$ is the output of industry k which is fixed at the pre-sample year 2000. This import penetration measure can be arguably considered as exogenous from the perspective of an individual firm as any firm's individual decision is unlikely to induce changes in aggregate industry imports. But still, an omitted variable bias cannot be ruled out: The surge in Chinese imports could be correlated with unobserved factors that are also related to both the UK's import demand and a firm's investment in innovation. To isolate the component of the growth of Chinese imports that is due to China's supply shocks, I adopt the IV strategy by Autor et al. (2020). Specifically, I exploit China's exports to 20 other developed economies ('$D20$') in the same year as an instrument for the UK's imports from China:[16]

[14] This transformation is ad-hoc but is still less problematic as R&D expenditures in this paper are 6-digit numbers (hundreds of thousands pounds sterling) on average and adding one to the original value does not seriously distort the overall distribution of R&D.

[15] This is particularly so when the investment in innovation incurs an upfront fixed cost.

[16] The countries used here are Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland and the USA.

$$\text{IV for } \text{IMP}_{k,t}^{CN} = \frac{\text{Export}_{k,t}^{CN \to D20}}{\text{Output}_{k,2000}}$$

where $\text{Export}_{k,t}^{CN \to D20}$ denotes China's exports to 20 advanced countries of industry k in year t. The underlying assumption in this identification strategy is that the high-income countries are similarly exposed to China's export supply shocks such as falling trade costs and expanding product variety.[17] Along with this IV strategy, I control for any unobserved sector-specific demand and/or technology shocks with 2-digit SIC sector by year dummies.

(Export demand) Next, I construct an exogenous firm-level measure of the export demand shock following Bombardini, Li and Wang (2018) and Aghion, Bergeaud, Lequien and Melitz (2018):

$$\text{EXD}_{f,t}^{nEU} = \sum_{p} \sum_{d} \omega_{f,p,d} \log(\text{World Export}_{p,d,t})$$

where $\text{World Export}_{p,d,t}$ denotes the world's total exports (excluding the UK) of HS 6-digit product p into non-EU destination d in year t. $\omega_{f,p,d} = \frac{\text{Export}_{f,p,d,2000}}{\sum_p \sum_d \text{Export}_{f,p,d,2000}}$ and $\text{Export}_{f,p,d,2000}$ is a UK firm f's average exports of product p to non-EU destination d over 1998-2000 (pre-sample period).

The key assumption in this identification is that the global trade flows (excluding the UK) into a given product-destination market (p,d) ($\text{World Export}_{p,d,t}$) reflects the overall demand changes in that market which are exogenous to an individual UK firm f. This measure then sums over the logarithm of the world exports across all the product-destination pairs weighted by the relative importance of each market in the firm f's total non-EU exports. The HMRC trade dataset enables us to construct this firm-specific exposure to demand changes in each product-destination market. Note that this firm-level weight is based on the average exports over the pre-sample period between 1998 and 2000 to circumvent endogenous changes in the firm's exports due to innovation. Therefore, time variation in this measure stems only from

[17] As a potential threat to this IV strategy, there is a possibility that unobserved technology shocks that are common to high-income economies including the UK may generate similar changes in demand for Chinese imports across these countries. As Hombert and Matray (2018) point out, however, the fast-growing Chinese exports observed in the 2000's are mainly driven by supply-side factors in China such as regulatory reforms and its entry into the WTO in 2001. Thus, what is captured by this instrument should be primarily the supply shock to China.

World Export$_{p,d,t}$. This export demand measure is highly correlated with the logarithm of firm exports (correlation of 0.602) and the export dummy (0.579), suggesting that it predicts the firm's current engagement in exporting very well.[18]

(Other controls) Apart from Chinese import penetration and firm-level export demand, the equation also includes firm-level imports (Import$_{f,t}$) as an additional trade variable. Its inclusion is is based on Bøler, Moxnes and Ulltveit-Moe (2015) who find that R&D and importing are complementary activities.[19] Related to the firm's own importing, it is also important to note that increasing availability of cheaper inputs from China may affect firms' innovation independently of the competition channel. I will further check this alternative channel explicitly by including firms' imports from China, together with Chinese competition. I add firm characteristics (Controls$_{f,t}$) such as firm size measured by the logarithm of employment, turnover growth and a dummy equal to one if the firm is foreign-owned in a given year. All the variables on the right-hand side of the equation are lagged by one year to alleviate simultaneity concerns.

By adding firm fixed effects (α_f), the analysis examines within-firm changes in R&D in response to trade shocks. As noted by Autor et al. (2020) and Lim, Trefler and Yu (2018), there is a possibility of pre-trends that cannot be explicitly controlled for since our R&D data does not allow us to trace as far back as the early 1990s - before China's rapid growth.[20] Moreover, there could be various unobservable shocks not directly related to

[18] I also test two variants of the export demand measure. First, I modify the benchmark measure above by scaling it by the firm's initial export intensity – the ratio of the firms' total non-EU exports to its turnover. And then, I run a regression that includes both unscaled and scaled export demand measures. The coefficient of the unscaled measure is highly significant while that of the scaled measure is not different from zero. Second, I construct a new measure of export demand at the SIC 4-digit industry level. In this case, the firm-level exposure weight is replaced by the industry-specific weight for each market. This industry-level measure has an advantage of accounting for export entry by firms that did not initially engage in exporting. But still, the response to an industry-level demand shock would be different between initially exporting and non-exporting firms. Thus, I add an interaction term between the industry-level export demand measure and a dummy for firms' initial export statuses as well. The results of estimating the specification with the industry-level export demand are reported in appendix table 3.B3.

[19] Under imperfect substitutability between domestic and imported inputs, firms may gain from input variety. Firms may also find the quality-adjusted prices of imported inputs from more productive foreign suppliers are lower than the domestic ones. Therefore, increasing use of imported inputs could raise the overall profitability which in turn encourages firm investment in productivity. R&D may also encourage importing. Assuming that importing incurs a fixed cost, R&D raises future profits, thereby making it more profitable to engage in importing to cut input costs.

[20] The R&D tax credit scheme was introduced for SMEs in 2000. My analysis covers the period from 2002 because it was only in 2002 when the scheme was extended to large corporations and the applications among SMEs increased for the sample size to be sufficient for analysis.

the trade shocks investigated in this paper. To tackle these issues, the equation includes a comprehensive set of fixed effects, beyond firm fixed effects. The sector by year fixed effects ($\delta_{s,t}$) are aimed at absorbing any unobserved technology shocks at the sector level as mentioned before. I further test region by year fixed effects ($\nu_{r,t}$). It is to account for the effect of, for instance, immigration of low-wage workers to specific UK regions that may affect firms' R&D decisions as a labor cost shock (Gray, Montresor and Wright (2020)).[21] In all estimations, I cluster standard errors by 4-digit SIC industry.[22]

3.4 Estimation results

This section presents estimation results. To summarize, I find robust evidence of the detrimental effect of Chinese import competition on UK firms' R&D investment. Export demand, by contrast, is found to significantly stimulate their R&D.

3.4.1 Baseline

Table 3.1 presents the baseline results. The coefficient for Chinese competition in column 1 is negative and statistically significant, suggesting that firms in industries more exposed to Chinese import competition reduced their R&D expenditures. This specification, and all following columns, control for firm fixed effects and time-varying firm controls including log employment, sales growth and a dummy for foreign ownership. Column 2 controls for sector by year fixed effects that absorb unobserved demand and/or technological shocks at the sector level. The coefficient becomes smaller in absolute terms (-6.142 $\rightarrow$ -4.305) but is still highly significant.[23] Column 3 introduces *firm-specific* export demand as another determinant for R&D and column 4 tests the most stringent specification, adding region by year fixed effects. The estimate for Chinese competition becomes slightly smaller but remains significant.

Column 5 implements an IV estimation exploiting China's exports to other advanced countries in the same industry to purge the supply-driven component of the rising Chinese imports. The first-stage F-statistic is 21, suggesting that the instrument is a strong predictor

[21] Gray, Montresor and Wright (2020) find that the increased supply of low-skill foreign workers from eight Central and Eastern European countries, driven by these countries' accession to EU in 2004, led to an increase in innovation by UK firms - primarily process innovation. The extent of immigration by these workers was largely different across UK regions and, interestingly, the paper finds a tendency of the immigrants to settle in areas where their compatriots were already settled.

[22] I also test two-way clustering by industry and year and find the results are almost the same.

[23] Changes in the size of coefficient for Chinese competition shows the quantitative importance of controlling for sectoral trends as emphasized by Autor et al. (2020).

of Chinese imports into the UK.[24] The 2SLS estimate for Chinese competition is very similar to the OLS counterpart in column 4 (-3.989 vs -3.925). To interpret, a one percentage point rise in Chinese import penetration is associated with a decline in UK firms' R&D spending by 3.9 percent on average. Finally, column 6 reports the IV estimation for a linear probability model using the R&D dummy as an outcome variable and shows that Chinese competition leads to a lower R&D participation.[25] All together, these results support the hypothesis of the negative Schumpeterian effect on UK firms facing the onslaught of low-cost Chinese imports.

As another important channel of trade impacts, I verify a stimulating role of export demand in firms' technology investment, in line with the prior literature including Lileeva and Trefler (2010), Bustos (2011) and Aghion, Bergeaud, Lequien and Melitz (2018). This indicates that an increase in the size of export markets raises the potential profits that firms could earn from investing in innovation. The statistically significant estimate of 0.064 means that a one percent increase in the measure of export demand is associated with a 6.4 percent increase in firm R&D. Recall that our measure of export demand uses global trade flows into each destination that are plausibly exogenous to individual firms, weighted by their initial exports. Therefore, it does not simply pick up a correlation but can be interpreted as a casual impact running from export demand towards R&D.[26]

I also find a positive association between firms' importing and their R&D spending, which is supportive of the complementarity hypothesis between imported inputs and R&D of Bøler, Moxnes and Ulltveit-Moe (2015).

At this stage, one may be interested in the relative importance of the two trade channels - import competition and export demand. I implement a simple quantification exercise of comparing the impacts of a one standard deviation increase of each trade shock. Based on the estimates from column 5, a one standard deviation increase in the exposure to Chinese competition is estimated to reduce UK firms' R&D expenditures by around 26 percent (=-3.925*0.067). Interestingly, a positive export demand shock of the same magnitude could

[24] All the first-stage F-statistics reported herein are Kleibergen-Paap Wald statistic which is robust to non-i.i.d errors. For the first-stage regression, see column 1 of appendix table 3.B2.

[25] Specifically, a one percentage point rise in import competition from China reduces the probability for a firm to undertake R&D by 0.34 percentage points. This impact of Chinese competition on the extensive margin of R&D appears to be rather small compared to the effect on the level of R&D. I also find a smaller estimate for Chinese competition from the Poisson Pseudo-Maximum Likelihood estimation (PPML) which is known to be more robust to outcome variables with many zeros such as R&D in log-linear specifications. For the PPML result, see the section 3.4.5 as well as appendix table 3.B5.

[26] The results using an industry-level measure of export demand are reported in appendix table 3.B3. I find that, while the industry-specific export demand measure is not significant, firms that are initially exporting positively respond to the export demand shock.

Table 3.1 Impact of Chinese import competition on firm R&D

	log(R&D)					I(R&D)
	OLS	OLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{IMP}^{CN}_{k,t-1}$	-6.142***	-4.305***	-4.235***	-3.989***	-3.925**	-0.343**
	(1.623)	(1.088)	(1.094)	(1.069)	(1.568)	(0.14)
$\text{EXD}^{nEU}_{f,t-1}$			0.067***	0.064***	0.064***	0.005***
			(0.013)	(0.013)	(0.013)	(11663)
$\log(\text{Import}_{f,t-1})$	0.074***	0.075***	0.071***	0.070***	0.070***	0.006***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.001)
$\log(\text{Employment}_{f,t-1})$	0.245***	0.251***	0.236***	0.218***	0.218***	0.016***
	(0.089)	(0.082)	(0.080)	(0.078)	(0.077)	(0.007)
$\Delta\log(\text{Turnover}_{f,t-1})$	0.030	0.030	0.027	0.032	0.032	0.002
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.005)
$\text{Foreign}_{f,t-1}$	-0.162	-0.153	-0.149	-0.166	-0.166	-0.015
	(0.149)	(0.151)	(0.150)	(0.149)	(0.149)	(0.013)
N Obs	28,966	28,966	28,966	28,966	28,966	28,966
Adj R2	0.412	0.414	0.415	0.416	-	-
First-stage F-stat	-	-	-	-	21.0	21.0
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓					
Sector-year FE		✓	✓	✓	✓	✓
Region-year FE				✓	✓	✓

Note: The dependent variable is either log R&D or an R&D dummy (I(R&D)). Columns 5 and 6 run 2SLS instrumenting for $\text{IMP}^{CN}_{k,t-1}$ only. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

more than compensate for the adverse impact of tougher competition: A one standard deviation rise in export demand boosts firms' R&D spending by about 55 percent (=0.064*8.609). Then, how large are these effects of trade-related shocks when compared to, for instance, firm size which is a key R&D determinant as documented in the literature? Note that a one standard deviation increase in firm size, measured by log employment, is associated with an increase in the R&D expenditure by about 31 percent (=0.218*1.402). It suggests that a change in the trade environment surrounding firms may exert an influence that is as large or even larger in absolute magnitudes than the firm size. And by comparison, when determining their R&D investment, firms are more responsive to the expansion of foreign markets than the shrinking share in their domestic market due to foreign competition.

Turning to other firm controls, sales growth and foreign ownership were not significant.

3.4.2 Chinese vs non-Chinese import competition

Is the rise of Chinese imports a unique competitive shock or does it simply reflect that overall foreign competition intensified over the last decades? To check this, I include a measure of import penetration from all other non-EU countries ($\text{IMP}^{non-CN}_{k,t-1}$) in combination with Chinese competition and compare their effects. Column 1 of table 3.2 reports an OLS result. Even after controlling for the contemporaneous changes in other non-Chinese imports, Chinese competition is found to significantly reduce firms' R&D investment. The estimate for non-Chinese import penetration, by contrast, is not different from zero. Column 2 runs 2SLS instrumenting for Chinese competition and the result is essentially the same. These imply that the drastic rise in Chinese imports, accelerated by its accession into the WTO in 2001, posed an unparalleled competitive threat to UK manufacturing firms, discouraging their innovation efforts. Further regressions with the R&D dummy as an outcome variable in columns 3 and 4 provide qualitatively similar results.

3.4.3 Accounting for firm's own imports from China

As previously noted, firms' own importing from China could separately affect the firms' innovations. For instance, a greater supply of cheaper Chinese intermediate inputs may improve profitability of firms, which in turn leads to investment in innovation. Alternatively, firms may choose to offshore labor-intensive parts of their production to China and put more resources into inventions of new high-tech products. Considering these possibilities, I check more explicitly whether the increased availability of Chinese imports by firms affected their R&D, independently of the import competition channel. To establish a casual impact, I build an instrument for firms' imports from China, again exploiting China's exports to other developed countries:

$$\text{IV for } \log(\text{Import}^{CN}_{f,t}) = \sum_p \psi^{CN}_{f,p} \log(\text{Export}^{CN\to D20}_{p,t})$$

where $\text{import}^{CN}_{f,t}$ denotes either firms' total import values from China or the number of HS 6-digit products imported from China (import variety). $\text{Export}^{CN\to D20}_{p,t}$ denotes China's exports of HS 6-digit product p to 20 advanced countries in year t. $\psi^{CN}_{f,p} = \frac{\text{Import}^{CN}_{f,p,2000}}{\sum_p \text{Import}^{CN}_{f,p,2000}}$ and $\text{Import}_{f,p,2000}$ is a UK firm f's average imports of product p from China over 1998-2000 (pre-sample period). Analogous to the instrument for Chinese competition, this firm-level instrument exploits the time variation in China's exports to 20 other advanced countries at the

Table 3.2 Chinese vs non-Chinese competition

	log(R&D)		I(R&D)	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-4.271***	-4.326**	-0.385***	-0.365**
	(1.076)	(1.986)	(0.089)	(0.180)
$\text{IMP}^{non-CN}_{k,t-1}$	0.361	0.371	0.024	0.020
	(0.649)	(0.824)	(0.059)	(0.076)
$\text{EXD}^{nEU}_{f,t-1}$	0.064***	0.064***	0.005***	0.005***
	(0.013)	(0.013)	(0.001)	(0.001)
$\log(\text{Import}_{f,t-1})$	0.070***	0.070***	0.006***	0.006***
	(0.010)	(0.010)	(0.001)	(0.001)
N Obs	28,966	28,966	28,966	28,966
Adj R2	0.416	-	0.4677	-
First-stage F-stat	-	17.7	-	17.7
Firm controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: Columns 2 and 4 run 2SLS instrumenting for Chinese competition. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

product level that are weighted by the share of product p in the UK firms' initial imports from China. I further include a binary indicator for firms' importing from other non-EU countries ($I(\text{Import}^{non-CN}_{f,t-1})$) to control for firms' importing statuses regardless of their imports from China.[27]

Column 1 in table 3.3 uses firms' import variety from China while column 2 uses firm's import values from China, each of which is instrumented for by the above-mentioned IV. For both measures, the firms' own importing from China does not have a significant impact on firms' R&D. By contrast, the Chinese competition – which is not instrumented for - remains negative and highly significant. Column 3 instruments for both Chinese competition and the firm's import values from China using the respective instruments. The impact of Chinese competition is essentially the same in magnitude and is significant at the 10% level while

[27]Looking at the first-stage regressions in columns 2 and 3 of appendix table 3.B2, the proposed instrument has a strong positive correlation with both firm's import variety and import values from China.

the coefficient for firms' own imports from China is again not different from zero.[28] These suggest that increased access to Chinese inputs, despite a possible cost-saving effect, did not lead firms to increase their R&D expenditure to offset the adverse impact of the competition channel.[29]

Table 3.3 IV estimation for firm-level imports from China

	log(R&D)			I(R&D)		
	(1)	(2)	(3)	(4)	(5)	(6)
$IMP^{CN}_{k,t-1}$	-4.266***	-4.142***	-4.480*	-0.377***	-0.372***	-0.365*
	(1.380)	(1.310)	(2.427)	(0.113)	(0.103)	(0.208)
$EXD^{nEU}_{f,t-1}$	0.065***	0.060***	0.060***	0.005***	0.005***	0.005***
	(0.014)	(0.019)	(0.019)	(0.001)	(0.002)	(0.002)
$\log(\text{Import variety}^{CN}_{f,t-1})$	0.741			0.032		
	(1.848)			(0.159)		
$\log(\text{Import value}^{CN}_{f,t-1})$		0.227	0.225		0.010	0.010
		(0.558)	(0.553)		(0.048)	(0.047)
$I(\text{Import}^{non-CN}_{f,t-1})$	0.516***	0.463**	0.464**	0.045***	0.043**	0.043**
		(0.113)	(0.213)	(0.010)	(0.018)	(0.018)
N Obs	28,966	28,966	28,966	28,966	28,966	28,966
First-stage F-stat	9.6	4.5	2.3	9.6	4.5	2.3
Firm controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓	✓	✓

Note: Columns 1 and 2, and columns 4 and 5 instrument for firms' imports from China - either $\log(\text{Import variety}^{CN}_{f,t-1})$ or $\log(\text{Import value}^{CN}_{f,t-1})$ - only. Columns 3 and 6 instrument for both $IMP^{CN}_{k,t-1}$ and $\log(\text{Import value}^{CN}_{f,t-1})$. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

[28]One needs a caution that the instrument is not strong for the firm's import values from China according to the first-stage F-statistic. The problem gets even worse when instrumenting for both firm-level import values from China and Chinese competition. This would be partly because the two instruments rely on similar sources of time variation - China's exports to other advanced countries.

[29]The offshoring hypothesis would not be pertinent to the firms in this analysis as many of these firms are small and medium-sized and thus would not engage in a multi-stage production process, any part of which is to be delegated to foreign affiliates. Bloom, Draca and Van Reenen (2015) also show mixed evidence on the impact of a Chinese input supply shock such that it did not increase firm patenting while positively affecting firm TFP and IT adoption.

3.4.4 Firm heterogeneity

We thus far document that import competition from China significantly hinders R&D while export demand encourages it for average UK firms. One interesting pattern emerging from the prior literature is that the innovation response to trade shocks varies across firms according to their initial productivity. This section explores the potential heterogeneity in R&D responses to both import competition and export demand shocks. Similarly to Bustos (2011) and Bombardini, Li and Wang (2018), I split firms into four groups based on the two-year lagged labor productivity within the 2-digit sector by year cells. Labor productivity herein is measured by turnover per employee.[30] $\mathrm{H}_{f,t-2}$ or $\mathrm{L}_{f,t-2}$ is defined as a dummy equal to one if the firm is above the 75th percentile or below the 25th percentile according to its two-year lagged productivity, respectively. I add the interaction terms between the two trade shocks with these dummies as follows:

$$\begin{aligned}\mathrm{RnD}_{f(k),t} = \;& \beta_1 \mathrm{IMP}^{CN}_{k,t-1} + \beta_2 \mathrm{IMP}^{CN}_{k,t-1} * \mathrm{H}_{f,t-2} + \beta_3 \mathrm{IMP}^{CN}_{k,t-1} * \mathrm{L}_{f,t-2} \\ & + \beta_4 \mathrm{EXD}^{nEU}_{f,t-1} + \beta_5 \mathrm{EXD}^{nEU}_{f,t-1} * \mathrm{H}_{f,t-2} + \beta_6 \mathrm{EXD}^{nEU}_{f,t-1} * \mathrm{L}_{f,t-2} \\ & + \beta_7 \mathrm{H}_{f,t-2} + \beta_8 \mathrm{L}_{f,t-2} + \gamma \log(\mathrm{Import}_{f,t-1}) + \mathrm{Controls}_{f,t-1} \\ & + \alpha_f + \delta_{s,t} + \nu_{r,t} + \varepsilon_{f,t}\end{aligned}$$

Columns 1 and 2 in table 3.4 report the results for log R&D and an R&D dummy, respectively.[31] There is no difference between more productive and less productive firms in their negative response to Chinese competition (the 2nd and 3rd rows). By contrast, I observe strong heterogeneity in their response to a positive export demand shock (the 6th and 7th rows). Specifically, firms sitting in the top quarter of the labor productivity distribution increase their R&D expenditure by around 40 percent (=0.037/(0.037+0.057)) more than average firms in response to the export demand shock. This suggests that more productive firms are better poised to take advantage of an increased foreign market demand relative to less productive firms.

[30] It would be ideal to use value-added instead of turnover in measuring labor productivity. But since information on individual firms' value-added is not available, I use turnover as a proxy.

[31] In the first-stage regressions, I use the interactions between the IV for Chinese competition and the productivity dummies ($\mathrm{H}_{f,t-2}$ and $\mathrm{L}_{f,t-2}$) as the instruments for $\mathrm{IMP}^{CN}_{k,t-1} * \mathrm{H}_{f,t-2}$ and $\mathrm{IMP}^{CN}_{k,t-1} * \mathrm{L}_{f,t-2}$.

Table 3.4 Firm heterogeneity (2SLS)

	log(R&D)	I(R&D)	log(R&D)	I(R&D)
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-3.652**	-0.339**	-7.227***	-0.553***
	(1.615)	(0.136)	(2.369)	(0.201)
$\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$	0.142	0.031		
	(2.069)	(0.180)		
$\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$	-0.598	0.013		
	(2.424)	(0.209)		
$\text{IMP}^{CN}_{k,t-1} * \text{E}_{f}$			5.183*	0.330
			(2.840)	(0.235)
$\text{EXD}^{nEU}_{f,t-1}$	0.057***	0.005***	0.059***	0.005***
	(0.014)	(0.001)	(0.013)	(0.001)
$\text{EXD}^{nEU} * \text{H}_{f,t-2}$	0.037***	0.003***		
	(0.011)	(0.001)		
$\text{EXD}^{nEU} * \text{L}_{f,t-2}$	-0.010	-0.001		
	(0.012)	(0.001)		
$\text{H}_{f,t-2}$	0.024	-0.001		
	(0.133)	(0.012)		
$\text{L}_{f,t-2}$	-0.066	-0.010		
	(0.148)	(0.013)		
$\log(\text{Import}_{f,t-1})$	0.068***	0.006***	0.070***	0.006***
	(0.010)	(0.001)	(0.010)	(0.001)
N of obs	28,966	28,966	28,966	28,966
First-stage F-stat	7.1	7.1	10.5	10.5
Firm controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: In the first-stage regressions for columns 1 and 2, I use the interactions between the IV for Chinese competition and the productivity dummies ($\text{H}_{f,t-2}$ and $\text{L}_{f,t-2}$) as the instruments for $\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$ and $\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$. Likewise, in the first-stages for columns 3 and 4, I use the interaction between the IV for Chinese competition and firms' initial exporting dummy (E_f) as the instruments for $\text{IMP}^{CN}_{k,t-1} * \text{E}_f$. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

As another source of firm heterogeneity, I test whether the competition effect varies over a firm's initial export status:

$$\begin{aligned}\text{RnD}_{f(k),t} = \; & \beta_1 \text{IMP}^{CN}_{k,t-1} + \beta_2 \text{IMP}^{CN}_{k,t-1} * \text{E}_f + \beta_3 \text{EXD}^{nEU}_{f,t-1} \\ & + \gamma \log(\text{Import}_{f,t-1}) + \text{Controls}_{f,t-1} + \alpha_f + \delta_{s,t} + \nu_{r,t} + \varepsilon_{f,t}\end{aligned}$$

where E_f denotes a dummy equal to one if firms exported at least once during the initial period (1998-2000). Column 3 in table 3.4 shows that firms with a prior exporting experience are less hurt by Chinese competition. The interaction term with the initial exporting dummy (the 4th row) is positive and significant at the 10% level. Quantitatively, the adverse impact of Chinese competition on R&D diminishes by more than half (-2.044 = -7.227 + 5.183) for the initially exporting firms, compared to -7.227 for average firms (the 1st row). This could be because firms that had already entered into exporting were better able to reallocate their sales abroad in the face of tougher foreign competition in domestic markets. The coefficient for the interaction term in the R&D dummy regression (column 4) is marginally insignificant, which implies that the advantage of initial exporting is more relevant for adjusting the level of R&D rather than R&D participation.

3.4.5 Robustness

To assess the robustness of the previous results, I begin by examining the importance of firm size. Specifically, columns 1 and 2 of appendix table 3.B4 run 2SLS excluding very small firms with employment of less than 10. And columns 3 and 4 run the same 2SLS dropping very large firms with employment of more than 500. All the results are very similar to the baseline result: The coefficient for Chinese competition is negative and significant while the coefficients for firms' own import and export demand are strongly positive. It suggests that our results are not driven by a group of firms of a certain size.

Next, I estimate via Poisson Pseudo-Maximum Likelihood (PPML) as an alternative empirical model.[32] Appendix table 3.B5 reports the results that are qualitatively similar to those from the baseline regressions.[33] Column 1 does not instrument for Chinese competition.

[32] As Guceri and Liu (2019) adopted, PPML is known to yield a more consistent estimator in the log-linear specifications when the outcome variable is characterized by a highly skewed distribution with a massive number of zeros like R&D.

[33] Due to convergence issues, our PPML estimation does not allow for the stringent sector by year and region by year fixed effects. Instead, I control for firm and year fixed effects.

The estimate for Chinese competition is negative and significant at the 5% level, confirming the adverse impact on firm R&D. But its absolute size becomes smaller (-1.88) compared to the OLS counterpart (-3.989 in column 4 of table 3.1). The estimate for export demand, positive and highly significant, is similar to the OLS result (0.064 vs 0.055). Column 2 implements the control function approach that includes the residual from the first-stage regression of Chinese competition into the second-stage PPML estimation. The estimate for Chinese competition is almost the same in size and is still significant at the 10% level. But note that the coefficient of the first-stage residual is not significant (0.027 with standard error of 1.396), implying that the Chinese competition measure is exogenous and thus the instrumental variable may offer no improvement for consistency with the PPML estimator.

Finally, I attempt to generalize the findings on Chinese competition by using the alternative BSD-R&D sample, which is not combined with the firm-level trade dataset. Despite the drawback of not accounting for firm-level imports and exports, this approach facilitates estimation for a larger number of firms by using the *industry-level* import competition for more firms. Appendix table 3.B6 reports the 2SLS results with 691 more firms included (4,107 $\rightarrow$ 4,798). The result confirms that Chinese competition significantly inhibited firm R&D. The estimate of -4.033 in column 1 is comparable to -3.925 from the benchmark sample. Column 2 tests potential heterogeneity across the firms' labor productivity. The coefficient of the interaction term for more productive firms (the 2nd row) becomes much greater, but is still marginally insignificant. Regressions using the R&D dummy in columns 3 and 4 provide similar results overall.

3.4.6 Comparison with the literature

Our finding on the stimulative role of export demand for R&D corroborates the evidence suggested in the previous literature. The heterogeneous effect of export demand in favour of more productive firms is also consistent with the recent findings in Aghion, Bergeaud, Lequien and Melitz (2018) on French firms.

Instead, the adverse impact of Chinese competition found in this paper, while in line with Autor et al. (2020), is at odds with Bloom, Draca and Van Reenen (2015). As Shu and Steinwender (2019) reviewed, empirical evidence remains divided over whether foreign competition encourages or discourages innovation. The difference from Bloom, Draca and Van Reenen (2015), among others, may be partly due to different types of firms considered.[34]

[34] It should also be noted that, while several papers use patenting as a measure of innovation, firm patenting may be geared up to protect their existing intellectual properties rather than new innovations. Firms might

Bloom, Draca and Van Reenen (2015) focus on the largest European firms whereas a great fraction of firms in this paper are small and medium sized. These smaller firms are likely to be more affected by the industry's exposure to import competition: In many cases, they would operate within a single industry and thus have little scope for diversification to spread out the competitive pressure.[35] Also noteworthy is the recent finding by Bloom, Romer, Terry and Van Reenen (2020) that even large European firms (the same firms used in Bloom, Draca and Van Reenen (2015)) experienced a significant decline in their sales growth facing Chinese competition, albeit increased patenting. The sales loss due to rising Chinese imports could have given much more pain to smaller firms since their R&D is likely to be more sensitive to cashflows unlike the large firms with more reserved resources. This could also explain why we do not observe a heterogeneous response to the competition shock across firm productivity unlike some previous studies.[36] In the context of the inverted U-shaped relationship between competition and innovation (Aghion et al. (2005)) - one theoretical model of heterogeneity, most firms in our analysis may not be technological leaders within their industries and thus are located on the downward-sloping line of the inverted U-shaped relationship where increased competition stifles innovation.

3.5 Concluding remarks

How firm innovation is affected by changes in the trade environment has been at the heart of the long-lasting debate on the consequence of globalization. Empirical evidence has been divided. Using administrative datasets for UK firms' R&D expenditure and their trade exposures, this paper investigates the impacts of import competition and export demand on firms' R&D investment. I find a strong, detrimental effect of foreign competition ramped up by Chinese imports on UK firms' R&D investment. Increased export demand, by contrast, significantly boosts firm R&D. While the quantitative significance of both channels are substantial, a one standard deviation export demand shock raises R&D by more than a Chinese competition shock of the same size reduces it. There is also evidence of heterogeneity

have a stronger incentive for this so called 'defensive patenting' in the face of increasing threats of imitation by Chinese competitors. For instance, Yamashita and Yamauchi (2020) finds that while Japanese firms increased patenting in the face of Chinese competition, the overall quality of the patents fell in terms of forward citations and the number of international patents. They argue that these findings are related to a defensive nature of patenting.

[35] As one interesting dimension of adjustment, Breinlich, Soderbery and Wright (2018) find that UK manufacturing firms shift their sales from goods to services in response to increasing import competition. And this goods-to-service adjustment takes place among large firms with a high initial R&D intensity.

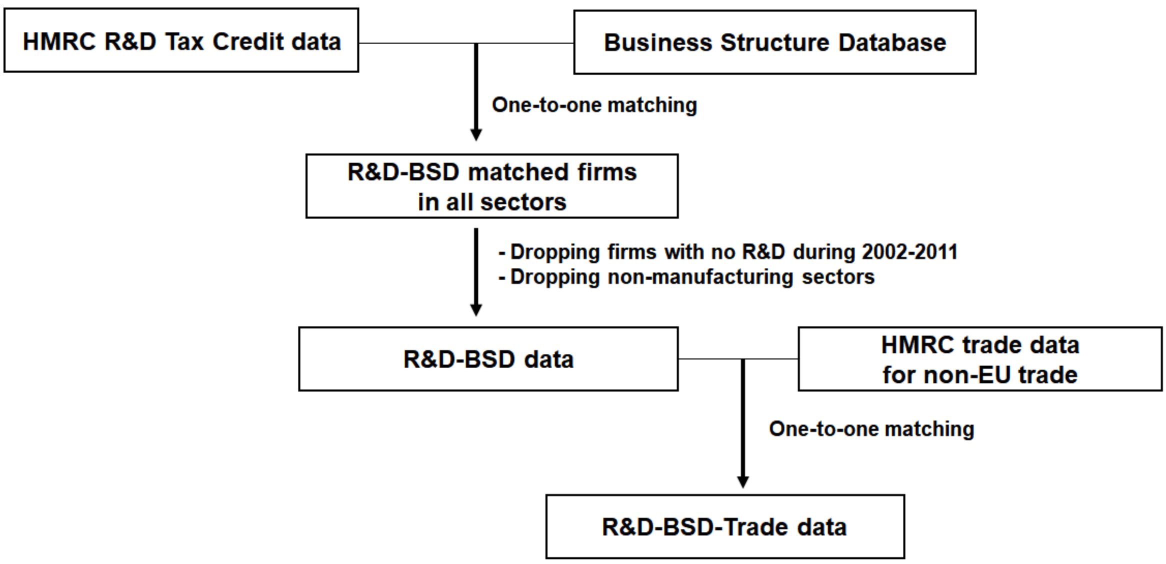
[36] For instance, see Fernandes (2007), Iacovone (2012) and Bombardini, Li and Wang (2018) who find heterogeneous effects of import competition on firm productivity or patenting.

in firms' R&D responses to each trade shock. First, firms that are initially exporting are less affected by competition from China. Second, firms with an initially higher productivity level respond more positively to the export demand shock. These findings together imply that innovation by purely domestic and less profitable firms was most negatively affected by globalization, leading to a widening productivity gap across firms.

Appendix 3.A Procedure for combining datasets

I combine the three administrative datasets using the look-up tables provided internally by HMRC Datalab across different firm identifiers.[37] One practical challenge is that a firm identifier in one dataset has many-to-many relationships with other identifiers from different datasets.[38] As the most conservative and transparent approach, I keep only a subset of firms whose identifiers are matched one-to-one with one another across datasets. This results in dropping some large firms with multiple identifiers in any of the datasets. I first merge the BSD and the R&D dataset for firms that are matched one-to-one between the two identifiers of each dataset. Among the matched pairs, I keep those in manufacturing sectors that reported non-zero R&D spending at least once between 2002 and 2011. I label the merged dataset up to this stage as 'BSD-R&D' dataset. Finally, I merge the BSD-R&D dataset with the trade dataset to construct the benchmark 'BSD-R&D-Trade' sample.

Fig. 3.A1 Flow of dataset construction

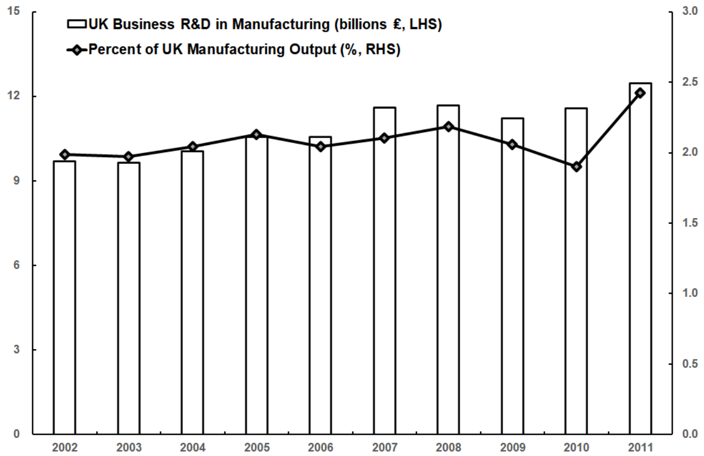


[37] The HMRC Datalab provides separate concordance tables for each pair of identifiers between the unique taxpayer reference number from the corporate tax dataset, enterprise reference number (Entref) from the BSD and value-added tax reference number (VRN). I first concord the Tradeid from the HMRC trade dataset into the VRN, which is then matched with the rest of the identifiers.

[38] As one notable example, firms' overseas transactions are reported at the value-added tax unit level, not at a consolidated national level. Large firms can also consist of multiple subsidiaries that each have own registration numbers. For these reasons, each identifier may have a many-to-many match with one another (Mion and Muuls (2015)).

Appendix 3.B Further statistics and results

Fig. 3.B1 UK Business R&D in manufacturing sectors



Note: The aggregate manufacturing R&D statistics herein are based on the publicly released Business Enterprise Research and Development (BERD), which is different from the qualifying R&D expenditures for HMRC tax reliefs. The manufacturing output is the sum of the UK manufacturing firms' turnovers in the BSD. Source: Office for National Statistics (ONS) and ONS Business Structure Database (BSD).

Table 3.B1 Descriptive Statistics

	BSD-R&D-Trade sample			BSD-R&D sample		
Variable	N	Mean	SD	N	Mean	SD
Turnover	33,958	7,671.6	68,291.5	39,736	8,850.7	67,584.3
Employment	33,958	52.1	239.9	397,36	59.3	235.8
Firm age	33,958	18.4	10.6	39,736	18.7	10.5
R&D expenditure	33,958	130.8	1204.4	39,736	160.9	1,802.6
R&D dummy	33,958	0.403	0.490	39,736	0.410	0.492
Non-EU import competition	33,958	0.114	0.138	39,736	0.111	0.133
Chinese import competition	33,958	0.027	0.067	39,736	0.026	0.064
Export to non-EU	33,958	1,418.6	13,300			
Import from non-EU	33,958	932.2	14,600			
Export dummy	33,958	0.653	0.475			
Import dummy	33,958	0.613	0.486			
Import from China	33,958	58.5	755.5			

Note: All variables are at the firm level except for non-EU and Chinese import competitions at the UK SIC 4-digit level. Turnover, R&D expenditure, exports and imports are in thousands of pounds sterling. Firm age is in years. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table 3.B2 First-stage regressions

	$\text{IMP}^{CN}_{k,t-1}$	$\log(\text{import variety}^{CN}_{f,t-1})$	$\log(\text{import value}^{CN}_{f,t-1})$
	(1)	(2)	(3)
IV for $\text{IMP}^{CN}_{k,t-1}$	0.031***		
	(0.007)		
IV for $\log(\text{import}^{CN}_{f,t-1})$		0.030***	0.098**
		(0.010)	(0.046)
N Obs	28,966	28,966	28,966
Other controls	✓	✓	✓
Firm FE	✓	✓	✓
Sector-year FE	✓	✓	✓
Region-year FE	✓	✓	✓

Note: Column 1 is the first-stage regression for column 5 of table 3.1. Columns 2 and 3 are the first-stage regressions for columns 1 and 2 of table 3.3, respectively. Each regression includes all other regressors in the second-stage regressions. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table 3.B3 Using the industry-level measure of export demand

	log(R&D)		I(R&D)	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-4.057***	-3.995**	-0.371***	-0.347**
	(1.059)	(1.529)	(0.089)	(0.137)
EXD $\text{sic}^{nEU}_{k,t-1}$	-0.030	-0.030	-0.003	-0.003
	(0.022)	(0.022)	(0.002)	(0.002)
EXD $\text{sic}^{nEU}_{k,t-1} * \text{E}_f$	0.063***	0.063***	0.005***	0.005***
	(0.012)	(0.012)	(0.001)	(0.001)
$\log(\text{Import}_{f,t-1})$	0.070***	0.070***	0.006***	0.006
	(0.010)	(0.010)	(0.001)	(0.001)
$\log(\text{Employment}_{f,t-1})$	0.220***	0.220***	0.016**	0.016**
	(0.079)	(0.078)	(0.007)	(0.007)
$\Delta \log(\text{Turnover}_{f,t-1})$	0.032	0.032	0.002	0.002
	(0.064)	(0.064)	(0.005)	(0.005)
$\text{Foreign}_{f,t-1}$	-0.171	-0.171	-0.015	-0.015
	(0.149)	(0.149)	(0.013)	(0.013)
	(0.117)	(0.117)	(0.010)	(0.010)
N Obs	28,966	28,966	28,966	28,966
adj R2	0.416	-	0.3716	-
First-stage F-stat	-	20.1	-	20.1
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: Columns 3 and 4 run 2SLS instrumenting for Chinese competition. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table 3.B4 Robustness to firm size (2SLS)

	Employment>10		Employment<500	
	log(R&D)	I(R&D)	log(R&D)	I(R&D)
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-4.630**	-0.378**	-4.051**	-0.350**
	(2.114)	(0.180)	(1.579)	(0.141)
$\text{EXD}^{nEU}_{f,t-1}$	0.063***	0.005***	0.063***	0.005***
	(0.022)	(0.002)	(0.013)	(0.001)
$\log(\text{Import}_{f,t-1})$	0.074***	0.006***	0.069***	0.006***
	(0.012)	(0.001)	(0.010)	(0.001)
$\log(\text{Employment}_{f,t-1})$	0.083	0.002	0.222***	0.016**
	(0.141)	(0.012)	(0.078)	(0.007)
$\Delta\log(\text{Turnover}_{f,t-1})$	0.070	0.004	0.029	0.002
	(0.100)	(0.008)	(0.063)	(0.005)
$\text{Foreign}_{f,t-1}$	-0.134	-0.012	-0.142	-0.013
	(0.162)	(0.014)	(0.155)	(0.014)
N Obs	20,464	20,464	28,635	28,635
First-stage F-stat	28.8	28.8	20.8	20.8
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: All columns run 2SLS instrumenting for Chinese competition. Columns 1 and 2 are from the sub-sample for firms with employment of more than 10 and columns 3 and 4 are for firms with employment of less than 500. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table 3.B5 Poisson Pseudo-ML estimation

	no-IV	IV
	(1)	(2)
$\text{IMP}^{CN}_{k,t-1}$	-1.887**	-1.896*
	(0.781)	(1.044)
$\text{EXD}^{nEU}_{f,t-1}$	0.055***	0.055***
	(0.015)	(0.015)
$\log(\text{Import}_{f,t-1})$	0.029***	0.029***
	(0.007)	(0.007)
$\log(\text{Employment}_{f,t-1})$	0.091	0.091
	(0.063)	(0.063)
$\Delta\log(\text{Turnover}_{f,t-1})$	-0.010	-0.010
	(0.035)	(0.035)
$\text{Foreign}_{f,t-1}$	-0.056	-0.056
	(0.116)	(0.115)
N Obs	28,966	28,966
1st-stage residual	-	0.027
		(1.396)
Firm FE	✓	✓
Year FE	✓	✓

Note: Column 2 implements the control function approach of adding the residual from the first-stage regression for Chinese competition as an additional regressor in the second-stage Poisson estimation. Robust standard errors in parentheses. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table 3.B6 Estimation from the larger BSD-R&D sample (2SLS)

	log(R&D)		I(R&D)	
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-4.033**	-4.461***	-0.348**	-0.399***
	(1.57)	(1.604)	(0.140)	(0.134)
$\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$		2.715		0.241
		(2.227)		(0.187)
$\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$		-0.353		0.027
		(2.347)		(0.203)
$\text{H}_{f,t-2}$		0.198*		0.014
		(0.107)		(0.009)
$\text{L}_{f,t-2}$		-0.155		-0.016
		(0.120)		(0.010)
$\log(\text{Employment}_{f,t-1})$	0.247***	0.263***	0.018***	0.02***
	(0.064)	(0.066)	(0.005)	(0.005)
$\Delta\log(\text{Turnover}_{f,t-1})$	0.067	0.114*	0.004	0.008
	(0.063)	(0.067)	(0.005)	(0.006)
$\text{Foreign}_{f,t-1}$	-0.152	-0.151	-0.014	-0.014
	(0.139)	(0.139)	(0.012)	(0.012)
N of obs	33,993	33,993	33,993	33,993
First-stage F-stat	24.0	8.0	24.0	8.0
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: This table is based on the BSD-R&D dataset - not combined with the firm-level trade dataset. In the first-stage regressions for columns 2 and 4, I use the interactions between the IV for Chinese competition and the productivity dummies ($\text{H}_{f,t-2}$ and $\text{L}_{f,t-2}$) as the instruments for $\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$ and $\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

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